IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received April 16, 2021, accepted May 12, 2021, date of publication May 17, 2021, date of current version May 24, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3081138

Robust Array Beamforming via an Improved Chicken Swarm Optimization Approach

LIN CUI, YIXIN ZHANG, AND YAMENG JIAO
School of Electronics and Information, Xi'an Polytechnic University, Xi'an 710048, China

Corresponding author: Yixin Zhang (872298549@qq.com)

This work was supported in part by the National Natural Science Foundation of China Youth Project under Grant 61901347, and in part by the Scientific Research Program Fund for Shaanxi Provincial Education Department Program under Grant 18JK0342.

ABSTRACT Robust array beamforming is a challenging task in radar, sonar and communications due to the influence of direction of arrival (DOA) mismatch and sensor position errors. However, how to enhance the robustness of beamforming is a key issue in antenna arrays. The current paper focuses on a novel approach called the improved chicken swarm optimization (ICSO) method to settle the optimization model of conventional linearly constrained minimum variance (LCMV) based on support vector machine (SVM) to against the mismatch problems as well as control the sidelobe level (SLL). As far as the ICSO method is concerned, considering that the particle swarm optimization (PSO) algorithm has outstanding convergence performance in the early iteration, the dominance of the alpha wolf in the grey wolf optimization (GWO) algorithm and the innovative mutual attraction mechanism in the firefly algorithm (FA), and we introduce these three strategies into the solution update method of conventional chicken swarm optimization (CSO) algorithm for achieving better optimization capability. Moreover, an operation of removing duplicate solutions is proposed to enhance the utilization of the population. In terms of the SVM-based LCMV beamforming algorithm, we adopt the so-called linear ε - insensitive loss function to reconstruct the final cost function of LCMV by penalizing the errors between the actual and ideal array responses. Finally, we conduct simulations to evaluate the performance of the swarm intelligent optimization algorithms under an ideal scenario without mismatch and an actual scenario with the mismatch, respectively. And the results demonstrate that the developed ICSO algorithm obtains excellent robustness for different scenarios compared to PSO, FA, GWO and CSO optimization algorithms.

INDEX TERMS Robust array beamforming, improved chicken swarm optimization, linearly constrained minimum variance, support vector machine, sidelobe level, steering vector errors.

I. INTRODUCTION

Robust adaptive beamforming has received considerable attention in the past years due to its necessity for radar, sonar, astronomy, wireless communications, medical imaging, audio signal processing and many other areas [1]–[3]. Robust adaptive beamforming techniques have the ability to adjust the weighted vectors according to complex environment changes [4], [5]. As we all know, minimum-variance-distortionless-response (MVDR) beamforming has attracted wide attention due to its excellent spatial resolution and interference suppression capability [6], [7]. Unfortunately, various error sources include the array element position disturbance and the arrival angle error in practical applications [8]–[10]. Because of unsatisfactory behaviors, the steering vector errors can reduce the array output signal-to-interference-plus-noise-ratio (SINR), which will result in a severe decline in MVDR performance [11]. Therefore, the challenge of improving the robustness of adaptive beamforming is a major direction under the undesired scenes.

During the past decades, a large number of approaches in the array signal processing literature have been presented. Among them, a common method of diagonal loading (DL) is generally employed due to its relatively acceptable performance [12]. Cox *et al.* [13] are the first to use the DL method for robust beamforming. Its core idea is to modify the covariance matrix in virtue of adding a small loading

The associate editor coordinating the review of this manuscript and approving it for publication was Liangtian Wan.

factor to the sampling covariance matrix. This method is considered an effective beamforming algorithm. However, the deficiency of the DL approach is that it makes the null of the adaptive beam pattern shallower, which reduces the interference suppression capability. In addition, there is no clear theoretical guidance for the selection of the DL factor based on the uncertainty of the expected steering vector [14]–[17]. Since then, a great number of solutions have been developed in order to enhance the robustness of the minimum variance beamformers. The DL method in [18] has the ability to constrain the uncertainty set of the steering vector and obtain the loading factor under the circumstances of the steering vector estimation error. From another point of view, if the estimation error for the steering vector is not accurate enough, the performance of beamformers will decline sharply or even fail totally [19], [20]. There is no doubt that many other robust beamforming methods have been carried out, such as the convex optimization-based method [21], the Bayesian beamformer [22], and the fuzzy-inference-based beamformer [23].

In terms of sidelobe level control, the approach in [24] is to incorporate multiple quadratic inequality constraints outside the main lobe beam pattern on the basis of the MVDR method. The sidelobe level is able to be under the specified value, but only in the desired scenario. SVM is a wonderful machine learning method with excellent generalization ability, which belongs to statistical learning theory [25]. And it has been widely used in the fields of pattern classification [26], function estimation [27] and regression analysis [28]. In this study, we focus on reformulating the minimum variance beamforming by incorporating additional inequality constraints to penalize sidelobe level, which has the same form as support vector regression. In the meantime, allowing a certain deviation in the expected signal direction [29]. However, the SVM solution is usually found through quadratic programming (QP) techniques. Here, we use the swarm intelligence optimization algorithms, which effectively settle the conventional analytical methods that produce ill-conditioned solutions.

In recent years, the emerging swarm intelligence optimization algorithms have increasingly become the focus of attention due to their rapid convergence rate, excellent global convergence and strong robustness. For these reasons, they have been widely used in beamforming technologies. For example, Todnatee *et al.* [30] utilize the genetic algorithm (GA)to synthesize the linear antenna array beam pattern with a lower SLL, and a maximum SLL of -20 dB can be achieved by means of this method. Nonetheless, it is not evaluated the stability of the algorithm. Li *et al.* [31] introduce the PSO algorithm to optimize the antenna array, which optimizes the spacing between the array elements to improve the beam collection efficiency. Nonetheless, the solution is not very good in terms of accuracy. Sharaqa *et al.* [32] use the FA to optimize the set of weights and positions for the circular antenna array. Although FA has better performance in reducing the SLL of the circular antenna array, the CPU time is longer. Saxena *et al.* [33] use the GWO algorithm to obtain the optimized antenna positions and current amplitudes in order to achieve the best pattern synthesis. This method provides a considerable enhancement to the optimization of the linear antenna array. Nonetheless, no evaluation is made for other types of antenna optimization. Li *et al.* [34] adopt improved biogeography-based optimization (BBO) to optimize the linear and circular antenna array beam patterns. Nonetheless, it does not provide the performance of the algorithm for the high-dimensional optimization problem. Li *et al.* [35] employ invasive weed optimization (IWO) to optimize the maximum SLL of the conical conformal array because this method has good efficiency and stability. Nonetheless, the convergence speed has limitations in some aspects. Sun *et al.* [36] adopt a cuckoo search (CS) algorithm to suppress the SLL of the large antenna array in 5G communications, and the maximum SLL and the total transmission power are collectively reduced. Nonetheless, there is no mention of the effectiveness of the introduced improvement factors. Sun *et al.* [37] combine the CS algorithm and the CSO algorithm to propose an algorithm called CSCSO, which is used to optimize the beam pattern of the virtual node antenna array. Nonetheless, the performance of CSCSO on the large antenna arrays is not studied. Among the similar algorithms, the conventional CSO [38] is a novel algorithm with a superior performance in recent years, which draws on the diversity of chicken movement methods to break the balance between randomness and determinism to find the optimal solution. Therefore, it has been favored by lots of engineering optimization fields. The fly in the ointment is that no such kind of algorithm can perfectly solve all optimization problems. Although the conventional CSO provides a commendable idea, each solution update method is not effective, which results in a decrease in the overall search ability of the algorithm [39], [40]. Hence, these circumstances above prompt us to propose an improved version of the conventional CSO algorithm for solving the SVM robust beamforming optimization model. Generally, the approach is deemed satisfactory if it has the ability to enhance the robustness of the beamformer significantly.

Generally speaking, our noteworthy technical contributions are introduced as follows:

1) A robust beamforming fitness function based on SVM is constructed, which minimizes the array output power and adopts a linear ε - insensitive loss function.
2) In order to overcome the deficiencies as mentioned above of the conventional CSO algorithm, we propose an ICSO algorithm to solve the beamforming problem in the case of steering vector mismatch, that is, under non-ideal conditions. First of all, ICSO introduces the solution of the GWO algorithm to improve the randomness and blindness caused by the normal distribution of the solution update method of the roosters in conventional CSO to provide a more effective search method. Secondly, on account of the solution update method of hens following roosters oversimplifies, and the position

of chicks is only determined by their mother hens, which is prone to fall into local optimum in the later iteration. Therefore, we introduce the attraction mechanism that can enrich the update methods of hens and chicks. It also plays an indispensable role in the optimization algorithm. Last but not least, a mechanism to remove duplicate solutions is proposed to improve the population diversity of the algorithm. By means of improved mechanism, ICSO can avoid premature convergence and jump out of the local optimal solution to the global.

3) We conduct multi-dimensional simulations to further confirm the robustness of the proposed ICSO algorithm for steering vector mismatch.

II. BACKGROUND

It is assumed that K narrowband signals come from the far-field, and the number of M isotropic sensors are distributed in a uniform linear array. The output of narrowband beamformer can be expressed as:

$$y = \boldsymbol{w}^{\mathrm{H}} \boldsymbol{x}(k) \tag{1}$$

where k is the time index, $\boldsymbol{w} = \left[\boldsymbol{w}_1, \boldsymbol{w}_2 \cdots \boldsymbol{w}_M\right]^{\mathrm{T}}$ is the weighted vector, $\boldsymbol{x}(k) = \left[\boldsymbol{x}_1(k), \boldsymbol{x}_2(k), \cdots, \boldsymbol{x}_M(k)\right]^{\mathrm{T}}$ is the complex vector of array observations, and $(\cdot)^{\mathrm{H}}$ and $(\cdot)^{\mathrm{T}}$ denote conjugate transpose and transpose, respectively. The observation data vector at time instant k is given by:

$$\begin{aligned} \boldsymbol{x}(k) &= \boldsymbol{s}(k) + \boldsymbol{i}(k) + \boldsymbol{n}(k) \\ &= s(k)\boldsymbol{a}(\theta_s) + \sum_{j=1}^{K_i} i_j(k)\boldsymbol{a}\left(\theta_{ij}\right) + \boldsymbol{n}(k) \end{aligned} \tag{2}$$

where K_i is the number of interference signals, and $s(k)$, $i(k)$, and $n(k)$ represent the signal, interference and noise vectors, respectively. Here, $s(k)$ and $i_j(k)$ are the signal and interference symbol samples. The signal and interference DOA are θ_s and $\theta_{ij}, j = 1, \cdots, K$, $a(\theta_s)$ and $a\left(\theta_{ij}\right)$ are the corresponding steering vectors. The design of the classical LCMV beamformer can be written as follows:

$$\min_{\boldsymbol{w}} w^{\mathrm{H}} \boldsymbol{R}_x \boldsymbol{w} \quad \text{subject to} \quad \boldsymbol{F}^{\mathrm{H}} \boldsymbol{w} = \boldsymbol{g} \tag{3}$$

where $\boldsymbol{R}_x = \frac{1}{N_0} \sum_{k=1}^{N_0} \left[\boldsymbol{x}(k)\boldsymbol{x}^{\mathrm{H}}(k)\right]$ is the sample covariance matrix, N is the number of snapshots, F is a matrix with the linear constraints, and g is a complex constant that measures the array response at the expected DOA. In particular, the value of g is equal to 1, indicating that the response remains constant in the direction of observation, and the LCMV beamformer is commonly referred to as MVDR beamformer. When there is an estimation error in DOA of the desired signal or imperfect array calibration, the MVDR beamformer is known to degrade substantially. The reason for this phenomenon is that the desired signal is considered as interference. The MVDR beamformer can be expressed as:

$$\min_{\boldsymbol{w}} \boldsymbol{w}^{\mathrm{H}} \boldsymbol{R}_x \boldsymbol{w} \quad \text{subject to} \quad \boldsymbol{w}^{\mathrm{H}} \boldsymbol{a}(\theta_s) = 1 \tag{4}$$

We employ additional inequality constraints to modify the LCMV beamforming problem to ensure that the array only responds within the angle error range of the steering vector, thereby improving the robustness against the mismatch of the steering vector. Let us consider the observational angle range of the array as $[0°, 180°]$, the DOA of signal and interference can be written as θ_p, $p = 1, \cdots, L$. L_1 is the number of samples from the range of $(\theta_s - \vartheta, \theta_s + \vartheta)$, and $L_2 = L - L_1$ is the number of samples from the range $(0°, \theta_s - \vartheta) \cup (\theta_s + \vartheta, 180°)$. The desired beamformer response can be established as:

$$y_p = \begin{cases} 0, & |\theta_i - \theta_s| > \vartheta \\ \operatorname{Re}(\boldsymbol{g}) + j\operatorname{Im}(\boldsymbol{g}), & |\theta_i - \theta_s| \leq \vartheta \end{cases} \tag{5}$$

where ϑ is the maximum angular error range of the steering vector. $\operatorname{Re}(\cdot)$ and $\operatorname{Im}(\cdot)$ on behalf of the real and imaginary parts of a scalar, vector, or matrix, respectively.

According to the theoretical characteristics of SVM, it is necessary to reconstruct the optimization model of the LCMV beamforming:

$$\min_{\boldsymbol{w}} \frac{1}{2} \boldsymbol{w}^{\mathrm{H}} \boldsymbol{R}_x \boldsymbol{w} + C \sum_{p=1}^{L} \left| \boldsymbol{y}_p - \boldsymbol{w}^{\mathrm{H}} \boldsymbol{a}\left(\theta_p\right) \right|_{\varepsilon} \tag{6}$$

where $\left|y_p - \boldsymbol{w}^{\mathrm{H}} \boldsymbol{a}\left(\theta_p\right)\right|_{\varepsilon} = \max\left\{0, \left|y_p - \boldsymbol{w}^{\mathrm{H}} \boldsymbol{a}\left(\theta_p\right) - \varepsilon\right|\right\}$ is known as ε - insensitive loss function, which allows errors of array response for the assumed signal arrival angle θ_s smaller than ε, and the parameter ε is a non-negative real number that is used to define the set of admissible solutions. C is also a non-negative regularization constant, which sets a tradeoff between the output power of the array and the punishment for the mismatch between the actual and desired array response with an absolute difference larger than ε. In order to apply the principle of SVM, the optimization problem needs to be rewritten under the circumstances of real variables. For this purpose, the minimization problem is reconstructed as:

$$L(\tilde{w}) = \frac{1}{2} \tilde{\boldsymbol{w}}^{\mathrm{T}} \tilde{\boldsymbol{R}}_x \tilde{\boldsymbol{w}} + C \sum_{p=1}^{2L} \left| \tilde{y}_p - \tilde{\boldsymbol{w}}^{\mathrm{T}} \bar{\boldsymbol{a}}(p) \right|_{\varepsilon} \tag{7}$$

where $\tilde{\boldsymbol{w}} \in R^{2M \times 1}$ is:

$$\tilde{\boldsymbol{w}}^{\mathrm{T}} = \left[\operatorname{Re}\left(\boldsymbol{w}^{\mathrm{T}}\right) \quad \operatorname{Im}\left(\boldsymbol{w}^{\mathrm{T}}\right) \right]$$

and $\tilde{\boldsymbol{R}}_{\mathrm{x}} \in R^{2M \times 2M}$ is:

$$\tilde{\boldsymbol{R}}_x = \begin{bmatrix} \operatorname{Re}(\boldsymbol{R}_x) & -\operatorname{Im}(\boldsymbol{R}_x) \\ \operatorname{Im}(\boldsymbol{R}_x) & \operatorname{Re}(\boldsymbol{R}_x) \end{bmatrix}$$

For the sake of notational simplicity, we define the steering vector and array response as:

$$\bar{\boldsymbol{a}}(p) = \begin{cases} \tilde{\boldsymbol{a}}\left(\theta_p\right), & p = 1, \cdots, L \\ \tilde{\boldsymbol{a}}'\left(\theta_p\right), & p = L+1, \cdots, 2L \end{cases}$$

$$\tilde{y}_p = \begin{cases} \operatorname{Re}\left(y_p\right), & p = 1, \cdots, L \\ \operatorname{Im}\left(y_p\right), & p = L+1, \cdots 2L \end{cases}$$

where $\tilde{\boldsymbol{a}}\left(\theta_p\right)$ and $\tilde{\boldsymbol{a}}'\left(\theta_p\right) \in R^{2M\times 1}$ can be expressed as:

$$\tilde{\boldsymbol{a}}^{\mathrm{T}}\left(\theta_p\right) = \left[\operatorname{Re}\left(\boldsymbol{a}^{\mathrm{T}}\left(\theta_p\right)\right) \quad \operatorname{Im}\left(\boldsymbol{a}^{\mathrm{T}}\left(\theta_p\right)\right)\right]$$
$$\tilde{\boldsymbol{a}}'^{\mathrm{T}}\left(\theta_p\right) = \left[\operatorname{Im}\left(\boldsymbol{a}^{\mathrm{T}}\left(\theta_p\right)\right) \quad -\operatorname{Re}\left(\boldsymbol{a}^{\mathrm{T}}\left(\theta_p\right)\right)\right]$$

III. SVM-BASED SOLUTION

Within the context of the current paper, our objective is to optimize the performance of the beamformer by determining a set of optimal weighted vectors to achieve a superior beam directivity and a lower maximum SLL. For this purpose, we come up with a novel ICSO method for the above optimization problem (7).

Suppose a set of optimal solutions obtained by the objective function (7) is:

$$\boldsymbol{w} = [w_1, w_2, \cdots, w_M] = \boldsymbol{A}_i e^{j\boldsymbol{\varphi}_i} \tag{8}$$

where the vector A and $\boldsymbol{\varphi}$ represent the modulus and phase of each element contained in the weighted vector, respectively. $A_i \leq 1, \varphi_i = 2\pi k_i, i = 1, 2, \cdots, M$. Accordingly, the search space of the weighted vector should satisfy $A_i \in (0, 1)$ and $k_i \in (0, 1), i = 1, 2, \cdots, M$.

Regarding $\boldsymbol{w} = [w_1, w_2, \cdots, w_M]$ as the complex weight vector corresponding to the i th chicken, and the constraint condition can be represented as:

$$\begin{cases} \sum_{i=1}^{M} \operatorname{Re}(w_i) = 1 \\ \sum_{i=1}^{M} \operatorname{Im}(w_i) = 0 \end{cases} \tag{9}$$

The specific implementation method is as follows:

$$a_i = \frac{\operatorname{Re}(w_i) + \dfrac{1}{M}}{\sum_{i=1}^{M}\left[\operatorname{Re}(w_i) + \dfrac{1}{M}\right]}$$
$$b_i = \operatorname{Im}(w_i) - \frac{1}{M}\sum_{i=1}^{M}\operatorname{Im}(w_i) \tag{10}$$

Here, a complex weighted vector $\boldsymbol{w} = [a_1 + jb_1, a_2 + jb_2, \cdots, a_M + jb_M]$ with constraints is obtained. Afterwards, the corresponding transformation with regard to the real and imaginary parts of the complex weighted vector is conducted by utilizing $\tilde{\boldsymbol{w}}^{\mathrm{T}} = [\operatorname{Re}(\boldsymbol{w}^{\mathrm{T}})\operatorname{Im}(\boldsymbol{w}^{\mathrm{T}})]$. In the end, the minimum value of the objective function (7) is determined by ICSO algorithm, and $\boldsymbol{w}$ obtained by transforming $\tilde{\boldsymbol{w}}$ corresponding to the minimum value is the optimal weighted vector.

IV. PROPOSED ICSO APPROACH

In this section, we focus on the proposed ICSO method, which is improved for conventional CSO to settle robust beamforming based on SVM. ICSO method combines the advantages of three swarm intelligence algorithms to promote optimization performance. Furthermore, an operation mechanism of removing duplicate solutions is proposed to enhance the utilization of the population. The specific process of the ICSO is presented as follows.

A. CHICKEN SWARM OPTIMIZATION

CSO is a new swarm intelligence optimization algorithm proposed in 2014, which effectively deals with the objective optimization problem by means of imitating the hierarchy order and the behavior of chickens. The primary regulations of conventional CSO are as follows:

1) A special hierarchy order exists within the chicken swarm, in which the roosters have the highest status and often play the role of the decision-maker, while the hens and chicks belong to the vulnerable groups, therefore, the hens live with their subordinate roosters and the chicks live with their mother hens.
2) The entire chicken swarm is divided into different groups. Each group contains a leading rooster, many hens dominated by rooster, and a number of chicks following mother hens. In spite of the departure or intrusion of any individual will temporarily disrupt the social order of the group, a new hierarchy will be established as soon as possible. In addition, competitions exist within and between different groups, principally manifested in the tendency of hens to forage as close as possible to the rooster in the same group. when the chickens from other groups invade their territory, the rooster will also act to protect their territory from invasion.
3) The objective function value is closely related to the internal hierarchical order, which is the basis for dividing the three roles in the chicken swarm. Specifically, the chickens with the optimum fitness value will be classified as roosters, the chickens with the worst fitness value will serve as chicks, and the rest will act as hens.
4) The partition cycle G is introduced to simulate the influence of the variation in the number of individuals in each group on its hierarchy order, which means that after each iteration G, the three roles will be periodically redistributed, and the hierarchy order of the chicken swarm will also be redefined.
5) In the iterative process, for achieving the target of getting close to the forage, the individuals move according to their respective roles and the corresponding position update formula. A new solution accompanies the movement of an individual, and the global optimal solution depends on chicken with the strongest foraging ability in the chicken swarm.

The CSO algorithm updates the solution in different ways depending on the role of the chickens. The specific implementation method is that the objective function values corresponding to the candidate solutions are arranged in ascending order. At this point, let us say that the smaller value of the objective function is, the better the solution will be. Then the update method of roosters is as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} \times \left(1 + Randn\left(0, \sigma^2\right)\right) \tag{11}$$

$$\sigma^2 = \begin{cases} 1 & f_i \leq f_k \\ \exp \dfrac{f_k - f_i}{|f_i| + \xi} & \text{otherwise} \end{cases} \tag{12}$$

where $Rand\left(0, \sigma^2\right)$ is a normal distribution function with the mean of 0 and variance of σ^2, f_i and f_k are the objective function values of i and k, $k \in [1, RN]$, and $k \neq i$ means that another rooster k different from ith, and RN is the number of roosters. ξ represents the smallest constant in the computer, and its function is to prevent the denominator from being 0.

In general, the foraging behavior of hens is led and constrained by the roosters within the same group. In the meantime, there is still a competitive relationship with other chickens, so the solution update method of hens can be designed as follows:

$$\begin{aligned} x_{i,j}^{t+1} = x_{i,j}^{t} &+ \exp\left(\frac{f_i - f_{r_1}}{|f_i| + \xi}\right) \times Rand \times \left(x_{r_1,j}^{t} - x_{i,j}^{t}\right) \\ &+ \exp\left(f_{r_2} - f_i\right) \times Rand \times \left(x_{r_2,j}^{t} - x_{i,j}^{t}\right) \end{aligned} \tag{13}$$

where $Rand$ is a random number in the interval [0, 1], r_1 represents the rooster in the group with ith hen, r_2 represents another rooster or hen other than the group with ith hen, that is to say, $r_1 \neq r_2$.

Chicks as the most vulnerable group in the chicken swarm. They can only forage just around their mother hens. Therefore, the solution update method of chicks can be described as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL \times \left(x_{m,j}^{t} - x_{i,j}^{t}\right) \tag{14}$$

where m is the mother hen followed by the ith chick, FL represents the foraging coefficient.

B. IMPROVED CHICKEN SWARM OPTIMIZATION

It is widely known that the conventional CSO method is a new algorithm proposed in recent years, which has many merits compared with other swarm intelligence algorithms. Nevertheless, due to the difficulty and complexity of the beamforming optimization issue, we find that the conventional CSO method has enormous limitations in deal with this matter [41]. As we all know, the conventional CSO algorithm makes full use of the hierarchical mechanism to improve the overall optimization performance of the algorithm. However, the efficiency of the update method of each solution in the chicken society is not excellent, which leads to the lack of exploration of the algorithm. Therefore, the PSO algorithm with fast convergence speed in the early stage of iteration, FA with novel attraction mechanism and GWO algorithm with similar internal hierarchical order to the chicken swarm are fully integrated into the conventional CSO algorithm. In addition, it is considered that the continuously updated candidate solutions may appear two identical solutions in the same iteration, which will generate a less diverse population and a lower utilization. Hence, the operation mechanism of removing duplicate solutions is introduced to increase the diversity of the population, thereby improving the optimization performance of the algorithm. The details of the major improvements to ICSO are presented in Algorithm 1.

Algorithm 1 ICSO

```
Parameter initialization;
Determine fitness function f(x);
Evaluate the fitness value of f(x);
while t < t_max do
    if t%G == 0 then
        sort the solutions according to f(x)
        Define the hierarchal order and relationship
    else
        for i = 1 to N do
            if ith solution is a rooster then
                Update x_i using Eq. (15);
            end if
            if ith solution is a hen then
                Update x_i using Eq. (19);
            end if
            if ith solution is a chick then
                Update x_i using Eq. (22);
            end if
            Evaluate the new solution;
            If the fitness value of new solution better than
            original, accept it, otherwise, reject it, accept
            the original solution.
        end for
        Remove the duplicate solution using Algorithm2;
    end if
end while
```

1) IMPROVED UPDATE METHOD OF ROOSTERS

In essence, the roosters are nearer to the optimal solution due to their dominant position in the population. Nevertheless, the solution update method of roosters in conventional CSO obeys the normal distribution, which has great randomness and blindness, thereby resulting in the lack of exploitation ability. For overcoming the defect, we introduce the solution update approach of the alpha wolf of GWO as the globe search mechanism to improve the search performance. Moreover, we also introduce the solution update approach of PSO to speed up the convergence rate.

By introducing the solution update approach of GWO and PSO, the improved update approach of roosters can be designed as follows:

$$x_{i,j}^{t+1} = gbest - H \times Q + X_v \tag{15}$$

$$Q = |\, T \times gbest - x_{i,j}^{t} \,|, \quad T = 2\, r_3 \tag{16}$$

$$H = 2\, br_4 - b \tag{17}$$

$$X_v = w_r \times v_{i,j}^t + r_5 \times \; Rand \; \times \left(pbest - x_{i,j}^t\right) + r_6 \times \; Rand \; \times \left(gbest - x_{i,j}^t\right) \tag{18}$$

where H and T are coefficient factors, and b is the convergence factor that linearly decreases from 2 to 0 as the number of iterations increases. Q is used to represent the distance between the current and the global optimal solution, r_3 and r_4 are both random numbers in the interval [0, 1], $V_{i,j}^t$ is the speed of ith rooster in the tth generation, $pbest$ and $gbest$ represent the local and the global optimal solution respectively, and r_5 and r_6 are learning factors. $w_r = (0.5 + Rand)/2$, that is, the value is in the interval [0.25,0.75], which is the inertia weight to improve the optimization performance.

2) IMPROVED UPDATE METHOD OF HENS

As a matter of fact, the hens can be regarded as vulnerable groups in the population. In other words, the hens are relatively far from the optimal position. In conventional CSO, the solution update approach of the hens is divided into two parts. The first part is that the hens follow the rooster in their own group, and the second part is that they also follow other roosters or hens in other groups. However, the operation of the following rooster in their own group oversimplifies, so that their exploration ability is insignificant. In terms of this issue, we introduce the FA with attraction mechanism into the update approach of hens, which is exactly similar to the principle of rooster attracting hens. This idea improves the optimization efficiency of the algorithm on the basis of enriching the original solution update approach.

By adopting the attraction mechanism of FA, the improved the update method of hens can be described as follows:

$$x_{i,j}^{t+1} = x_{i,j}^t + \beta \times \left(x_{r_1,j}^t - x_{i,j}^t\right) + \alpha \times \zeta + S_2 \times Rand \times \left(x_{r_2,j}^t - x_{i,j}^t\right) \tag{19}$$

$$\beta = e^{\gamma \times r^2} \tag{20}$$

$$r = \left\| x_{r_1} - x_i \right\| = \sqrt{\sum_{j=1}^{d} \left(x_{r_1,j} - x_{i,j}\right)^2} \tag{21}$$

where β represents the attraction coefficient, γ indicates the light absorption coefficient, which is a random number in the interval [0.1, 10], and r manifests the Cartesian distance between r_1 and i. As the step size, α is a random number on the interval [0, 1]. ζ is a random number generated from a normal distribution.

3) IMPROVED UPDATE METHOD OF CHICKS

As we all know, the solution update methods of chicks are only determined by their corresponding mother hens, which is prone to fall into local optimum in the later iteration. This mechanism is particularly easy to make the chicken deviate from the optimal solution. Given this, we employ the FA with attraction mechanism into the update method of chicks, which will prompt the algorithm to effectively jump out of the local optimal solution, thereby obtaining the global optimal solution. Then, the improved update method of chicks is as follows:

$$x_{i,j}^{t+1} = x_{i,j}^t + \beta \times \left(x_{m,j}^t - x_{i,j}^t\right) + \alpha \times \zeta \tag{22}$$

4) THE OPERATION OF REMOVING DUPLICATE SOLUTIONS

Specifically, in the iterative process where the candidate solutions are constantly updated, there may be two identical solutions in the candidate solution set in the same iteration, which will reduce the diversity and utilization of the population, thereby leading to a poorer performance. Within the context of the current section, in order to improve the update efficiency of the respective solutions in CSO algorithm, we introduce an operation mechanism to remove the duplicate solutions, which finds out the duplicate solutions by comparing the candidate solutions sorted according to the merits and demerits of the objective function values. Then, a new candidate solution is randomly generated to replace it, which may enhance the effectiveness of the algorithm. The steps of the operation mechanism to remove the duplicate solutions are presented in Algorithm 2.

Algorithm 2 Remove Duplicate Solution Mechanism

```
for i = 1 to N do
    Rank in descending order for each dimension of x_i;
    Acquire a new solution x_ii;
    for j = i+1 to N do
        Rank in descending order for each dimension of
        x_j;
        Acquire a new solution x_jj;
        if x_ii==x_jj then
            Elect the value of x_jj from the same dimension
randomly;
        end if
    end for
end for
```

V. COMPUTER SIMULATIONS

In order to assess the performance of the proposed ICSO algorithm for application in the field of beamforming techniques, several simulations have been carried out in the desired scenario without steering vector mismatch and the practical circumstances with steering vector mismatch. Here, we suppose that a uniform linear array with $M = 16$ sensors and the isotropic sensors are arranged by a half wavelength, that is, $d = \lambda/2$, where the wavelength is denoted by the symbol λ. All signals are independent and the noise is Gaussian white noise. In this section, the SVM-based beamforming algorithm employs Vapnik's linear ε - insensitive loss functions. The signal -to noise rate (SNR) is set to 10 dB, and the interference-to-noise-rate (INR) is set to 30 dB. The actual signal DOA is 90°, and the DOAs of the interferences are 30°, 70° and 130°. The snapshots are set to 500, the parameters C and ε are set to 1 and 0.001, respectively. The uncertainty region ϑ is set equal to 2°, the observational angle

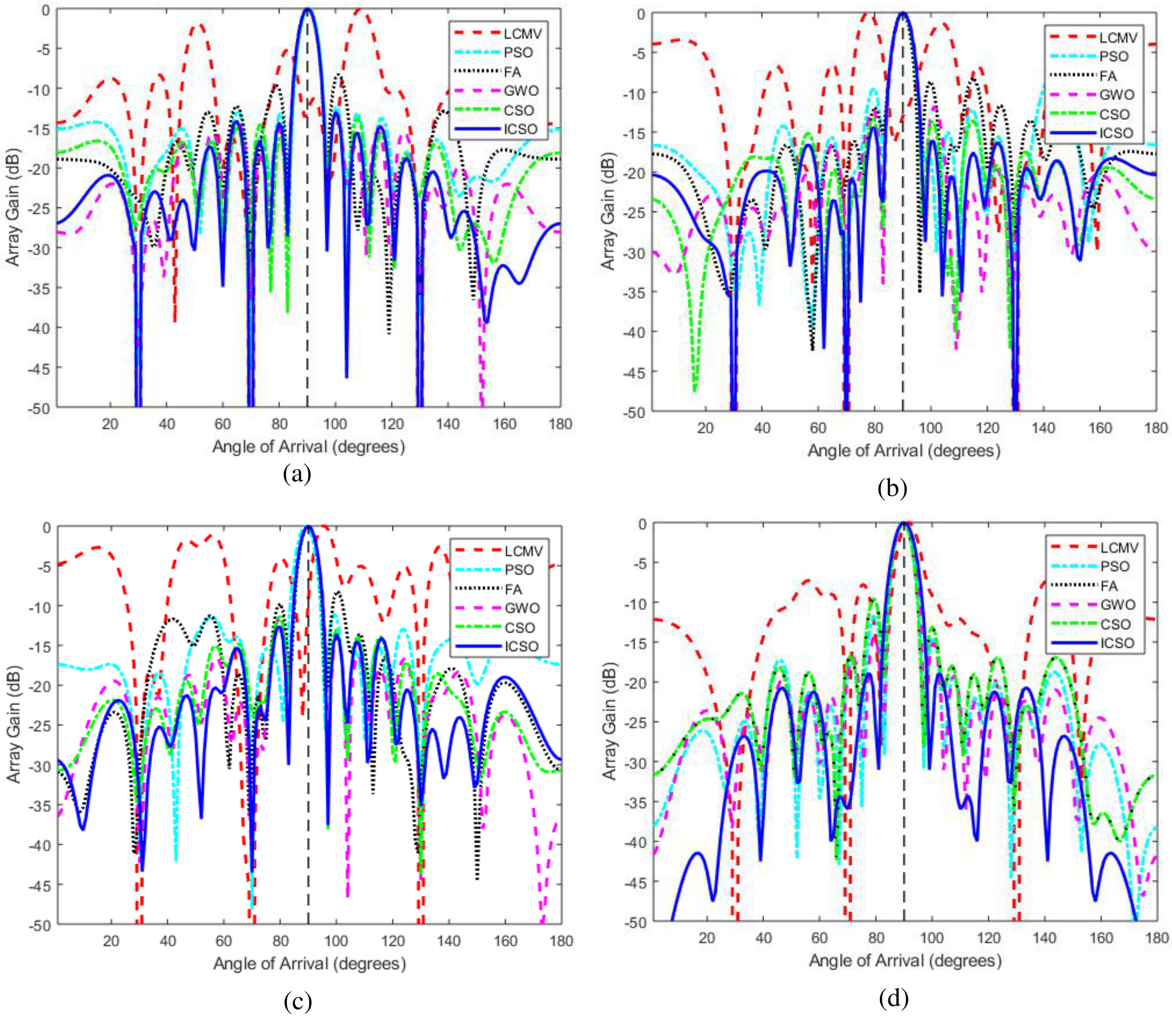


FIGURE 1. The beam patterns.

range [0°, 180°] is sampled uniformly at different intervals, L_1=20 angles are set from [88°, 92°], and L_2 = 40 angles are obtained from (0°, 88) ∪ (92°, 180°).

We utilize swarm intelligence optimization algorithms to solve the SVM-based beamforming technique. In order to compare the application performance of PSO algorithm, FA, GWO algorithm, CSO algorithm and ICSO algorithm in the beamforming field, we set the following parameter as TABLE 1:

A. THE BEAM PATTERNS

In experiment 1, we simulate the beam patterns without steering vector mismatch and the practical circumstance with steering vector mismatch, respectively. Afterwards, the performance of PSO algorithm, FA, GWO algorithm, CSO algorithm and ICSO algorithm in the beamforming field is compared in Fig. 1, where Fig. 1(a) displays the beam pattern in an ideal scenario without steering vector mismatch, Fig. 1(b) displays the beam pattern in an actual scenario with 2° of mismatch in the signal-of-interest DOA, Fig. 1(c) shows the beam pattern in an actual scenario with 0.02λ of mismatch in the standard deviation for position perturbation, and Fig. 1(d) demonstrates the beam pattern in an actual

TABLE 1. The key parameters setups of five optimization methods.

Algorithm	Values of the parameters
PSO[31]	$C_1 = 2, C_2 = 2, w_{pso} = 1$
FA[32]	$\alpha = 0.25, \beta = 0.5, \gamma = 1$
GWO[33]	$b \in [0,2], T \in [0,2], H \in [-2,2]$
CSO[38]	$RN = 0.2 \times N, HN = 0.6 \times N,$ $CN = N - RN - HN, MN = 0.1 \times N, G = 2,$ $FL \in [0.5, 0.9]$
ICSO	$RN = 0.2 \times N, HN = 0.6 \times N,$ $CN = N - RN - HN, MN = 0.1 \times N, G = 2,$ $\gamma = 1, w_r \in [0.25, 0.75], r_5 = 2, r_6 = 2,$ $b \in [0,2], T \in [0,2], H \in [-2,2]$

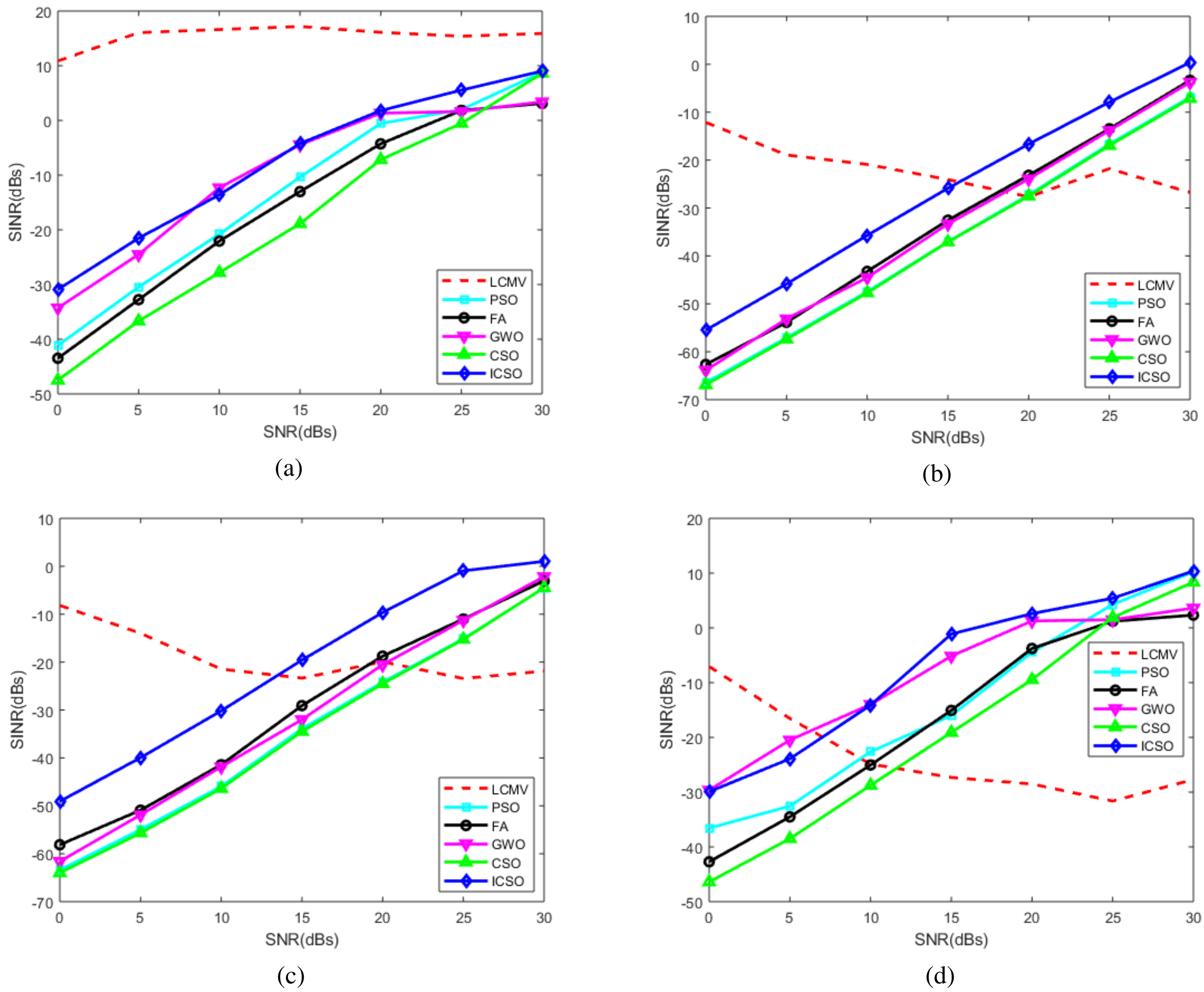


FIGURE 2. **The patterns of SINR with SNR.**

scenario with 0.20λ of mismatch in the standard deviation for position perturbation. For the sake of a simple notation, we denote the symbols of the intelligent optimization algorithms applied to robust beamforming as PSO, FA, GWO, CSO and ICSO, respectively. For convenience, place the sensors on the Z-axis, the position of the sensors has random positional disturbances in the Y and Z directions, and the disturbance is an independent zero-mean Gaussian random variable.

As can be seen from Fig. 1, due to the existence of the desired signal in the training data cell, the performance of the LCMV beamformer turns extremely worse, yet it always has deep nulls at the DOAs of the interferences in any case. Under the ideal scenario without mismatch, the other five SVM-based intelligence algorithms can obtain prominent main lobe beam pointing. In terms of sidelobe level, the FA obtains the weakest performance with the highest sidelobe level. On the contrary, ICSO achieves the lowest sidelobe level with the greatest performance. In the aspect of interference suppression, the strength of the GWO and ICSO are neck and neck, and both of them the outstanding interference suppression ability. Although the other three algorithms can suppress interference, their ability to suppress interference is not strong. The other three algorithms also have the ability to suppress interference, whereas the effect is obviously inferior to those two algorithms. In the actual situation of mismatch, the sidelobe of the beam will be distorted to varying degrees as the position disturbance deviation increases, and in the meanwhile, the ability to suppress interference is also declined. Nevertheless, the ICSO still has the lowest sidelobe level. In summary, it is proved that the application of ICSO to robust beamforming is based on inheriting the characteristics of the conventional LCMV algorithm and combining the merits of SVM to make the method more robust.

B. THE PATTERNS OF SINR WITH SNR

The simulation scenario of experiment 2 is the same as experiment 1, which expresses the relationship between output SINR and input SNR.

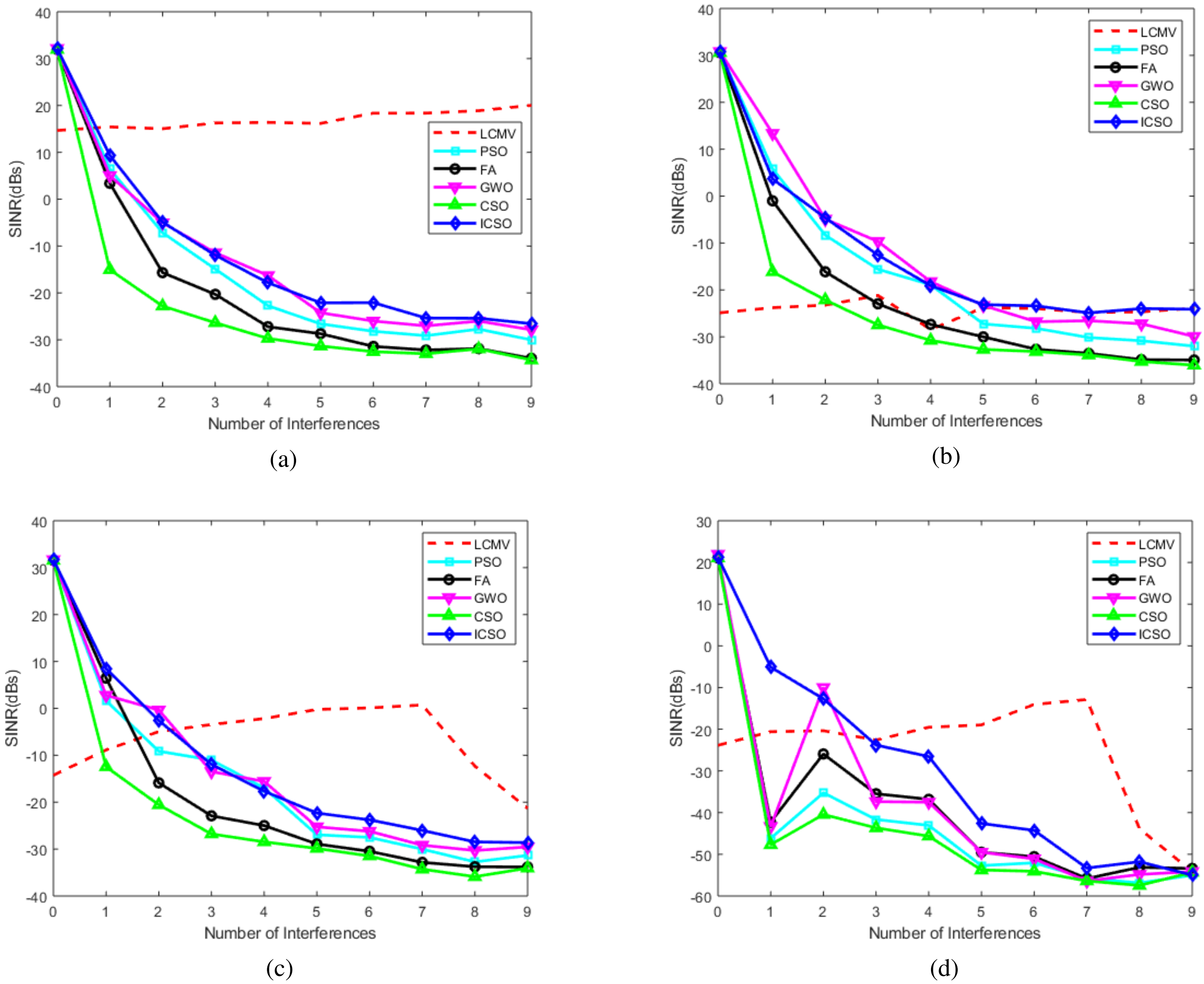


FIGURE 3. The patterns of SINR with interferences.

Observing the diagrams in Fig. 2, we can highlight that the swarm intelligence optimization algorithms achieve a superior performance than LCMV under the higher input SNR with the mismatch in the steering vectors, especially the ICSO method. However, there is no doubt that LCMV displays an extremely powerful performance with the highest output SINR in an ideal scenario. Once the mismatch occurs, the output SINR of LCMV gradually decreases with the input SNR increase, thereby generating performance degradation. However, the preponderances of the other five SVM-based swarm intelligence optimization algorithms are manifested in the scenario of the higher input SNR with the mismatch in the steering vectors, and the output SINR is gradually increased along with the increase of the SNR no matter an ideal scenario without mismatch or an actual condition with the mismatch. Compared with the other four swarm intelligence optimization algorithms, ICSO has a better performance with the highest output SINR. It is found that the output SINR of the SVM-based ICSO beamforming method has a superior robust performance when the SNR is higher.

C. THE PATTERNS OF SINR WITH INTERFERENCES

The objective in our third experiment is to verify the variation between output SINR and the number of interference, where the simulation scenario is the same as experiment 1.

As for Fig. 3, it is found that the performance of LCMV in a scenario without mismatch is quite stable, and the output SINR of the beamformer is hardly affected by the number of interference. In addition, for the 2° angle error in the steering vector, the LCMV method still has significant stability, while the output SINR of the beamformer is not as superior as before. However, once the mismatch occurs, the output SINR gradually decreases with the increase of the number of interference, which makes the performance of the beamformer worse. In view of the other five swarm

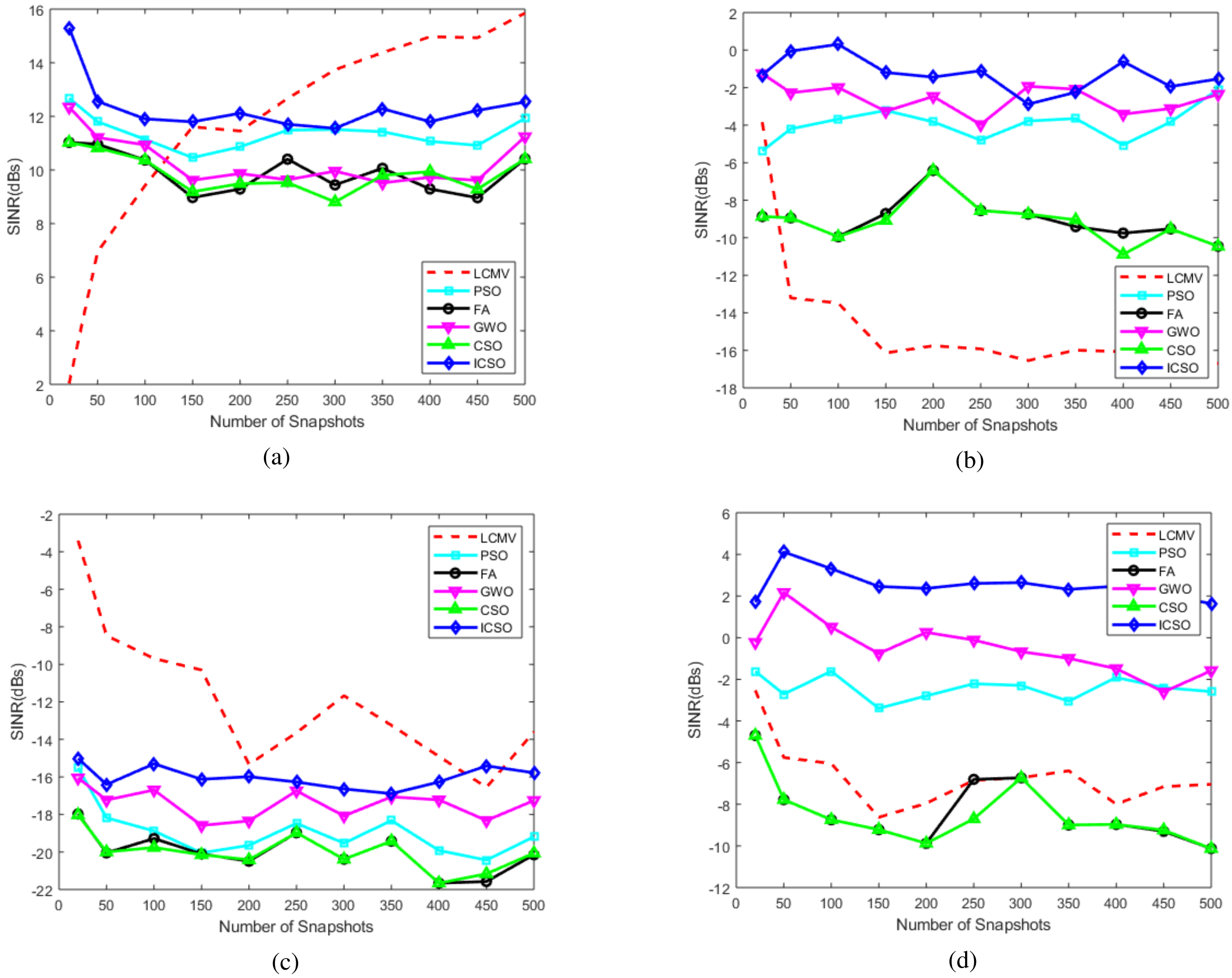


FIGURE 4. **The patterns of SINR with Snapshots.**

intelligence optimization algorithms, we can demonstrate that their output SINR exhibits a downward trend as the number of interference increases. Besides, whether the scenario is perfect or not, all of them can display superior performance in a scenario with less interference. In the aspect of searching for the optimal solution, ICSO is the leader of the other four algorithms. It directly indicates that the output SINR of ICSO for SVM-based has superior robust performance under a small amount of interference.

D. THE PATTERNS OF SINR WITH SNAPSHOTS

Similar to the scenario of the previous three experiments, in our fourth experiment, which reveals the changes between output SINR and the number of snapshots.

As can be obviously understood from Fig. 4, in an ideal scenario without mismatch in the steering vector, the output SINR of LCMV appears an upward trend as the number of snapshots increases, and the performance of the beamformer is fine. Once there is a mismatch, the output SINR drops sharply as the number of snapshots increases, and the performance of the beamformer deteriorates. Nevertheless, regardless of an ideal scenario without mismatch or an actual situation with the mismatch, the output SINR of the other five SVM-based swarm intelligence optimization algorithms will not change significantly as the number of snapshots increases, thereby showing the extremely stable performance. Compared with the other four swarm intelligent optimization algorithms, the SVM-based ICSO algorithm has the highest output SINR. It shows that the beamforming method based on SVM is not sensitive to the variation of the snapshots, and the perfect cooperation with the ICSO makes the beamformer demonstrate more superior performance.

VI. CONCLUSION

In this study, the conventional LCMV beamformer is redesigned as a support vector regression problem, and then the proposed ICSO approach is employed to settle the robust beamforming. The target includes the following contents: a) enhancing the robustness of the beamformer against errors in array response caused by misalignment in the steering vector. b) restraining and controlling the sidelobe level of the beam. We consider using the linear ε - insensitive loss function, and selecting the appropriate penalty parameter. Then, the proposed ICSO method is adopted to solve the robust beamforming ultimately. Computer simulation indicates that regardless of whether the steering vector is mismatched, the ICSO for SVM-based has satisfactory performance. Especially in the situation of higher SNR and lower number of interference signals.

The authors believe this study is just a small step in the design of robust beamforming solutions. Future work should improve the robustness of beamforming in multiple interference situations.

REFERENCES

[1] J. Xu, G. Liao, L. Huang, and H. C. So, "Robust adaptive beamforming for fast-moving target detection with FDA-STAP radar," *IEEE Trans. Signal Process.*, vol. 65, no. 4, pp. 973–984, Feb. 2017.

[2] H. Cho, J. Gu, and S.-C. Yu, "Robust sonar-based underwater object recognition against angle-of-view variation," *IEEE Sensors J.*, vol. 16, no. 4, pp. 1013–1025, Feb. 2016.

[3] J. Dang, Z. Zhang, and L. Wu, "Joint beamforming for intelligent reflecting surface aided wireless communication using statistical CSI," *China Commun.*, vol. 17, no. 8, pp. 147–157, Aug. 2020.

[4] H. R. Johnson and T. M. Khoshgoftaar, "Robust adaptive beamforming based on low-rank and cross-correlation techniques," *IEEE Trans. Signal Process.*, vol. 64, no. 15, pp. 3912–3919, Aug. 2016.

[5] F. Shen, F. Chen, and J. Song, "Robust adaptive beamforming based on steering vector estimation and covariance matrix reconstruction," *IEEE Commun. Lett.*, vol. 19, no. 9, pp. 1636–1639, Sep. 2015.

[6] M. Wax and Y. Anu, "Performance analysis of the minimum variance beamformer," *IEEE Trans. Signal Process.*, vol. 44, no. 4, pp. 928–937, Apr. 1996.

[7] J. Capon, "High-resolution frequency-wavenumber spectrum analysis," *Proc. IEEE*, vol. 57, no. 8, pp. 1408–1418, Aug. 1969.

[8] K. I. Pedersen, P. E. Mogensen, and B. H. Fleury, "A stochastic model of the temporal and azimuthal dispersion seen at the base station in outdoor propagation environments," *IEEE Trans. Veh. Technol.*, vol. 49, no. 2, pp. 437–447, Mar. 2000.

[9] L. Godara, "The effect of phase-shifter errors on the performance of an antenna-array beamformer," *IEEE J. Ocean. Eng.*, vol. OE-10, no. 3, pp. 278–284, Jul. 1985.

[10] J. Zheng, T. Yang, H. Liu, and T. Su, "Efficient data transmission strategy for IIoTs with arbitrary geometrical array," *IEEE Trans. Ind. Informat.*, vol. 17, no. 5, pp. 3460–3468, May 2021.

[11] M. Wax and Y. Anu, "Performance analysis of the minimum variance beamformer in the presence of steering vector errors," *IEEE Trans. Signal Process.*, vol. 44, no. 4, pp. 938–947, Apr. 1996.

[12] Y. Zhang, D. Sun, and D. Zhang, "Robust adaptive acoustic vector sensor beamforming using automated diagonal loading," *Appl. Acoust.*, vol. 70, no. 8, pp. 1029–1033, Aug. 2009.

[13] H. Cox, R. Zeskind, and M. Owen, "Robust adaptive beamforming," *IEEE Trans. Acoust., Speech, Signal Process.*, vol. ASSP-35, no. 10, pp. 1365–1376, Oct. 1987.

[14] O. Besson and F. Vincent, "Performance analysis of beamformers using generalized loading of the covariance matrix in the presence of random steering vector errors," *IEEE Trans. Signal Process.*, vol. 53, no. 2, pp. 452–459, Feb. 2005.

[15] J. Li, P. Stoica, and Z. Wang, "On robust capon beamforming and diagonal loading," *IEEE Trans. Signal Process.*, vol. 51, no. 7, pp. 1702–1715, Jul. 2003.

[16] S. A. Vorobyov, A. B. Gershman, and Z.-Q. Luo, "Robust adaptive beamforming using worst-case performance optimization: A solution to the signal mismatch problem," *IEEE Trans. Signal Process.*, vol. 51, no. 2, pp. 313–324, Feb. 2003.

[17] R. G. Lorenz and S. P. Boyd, "Robust minimum variance beamforming," *IEEE Trans. Signal Process.*, vol. 53, no. 5, pp. 1684–1696, May 2005.

[18] J. Li, P. Stoica, and Z. Wang, "On robust capon beamforming and diagonal loading," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, vol. 5, Apr. 2003, pp. 334–337.

[19] J. Zheng, R. Chen, T. Yang, X. Liu, H. Liu, T. Su, and L. Wan, "An efficient strategy for accurate detection and localization of UAV swarms," *IEEE Internet Things J.*, early access, Mar. 8, 2021, doi: 10.1109/JIOT.2021.3064376.

[20] J. Zheng, T. Yang, H. Liu, T. Su, and L. Wan, "Accurate detection and localization of UAV swarms-enabled MEC system," *IEEE Trans. Ind. Informat.*, vol. 17, no. 7, pp. 5059–5067, Jul. 2021, doi: 10.1109/TII.2020.3015730.

[21] Y. Chen, F. Wang, J. Wan, and G. Li, "Convex optimization based robust adaptive beamforming for underwater sensor array," in *Proc. IEEE 13th Int. Conf. Signal Process. (ICSP)*, Nov. 2016, pp. 1661–1665.

[22] K. L. Bell, Y. Ephraim, and H. L. Van Trees, "A Bayesian approach to robust adaptive beamforming," *IEEE Trans. Signal Process.*, vol. 48, no. 2, pp. 386–397, Feb. 2000.

[23] A. Morell, A. Pascual-Iserte, and A. I. Pérez-Neira, "Fuzzy inference based robust beamforming," *Signal Process.*, vol. 85, no. 10, pp. 2014–2029, Oct. 2005.

[24] J. Liu, A. B. Gershman, Z.-Q. Luo, and K. M. Wong, "Adaptive beamforming with sidelobe control: A second-order cone programming approach," *IEEE Signal Process. Lett.*, vol. 10, no. 11, pp. 331–334, Nov. 2003.

[25] G. Mahmoud, A. Omar, and O. Mohmoud, "Novel overlap method to eliminate vector deviation error in SVM of current source inverters," *IEEE Trans. Power Electron.*, vol. 33, no. 1, pp. 299–312, Jan. 2018.

[26] G. M. Borkar, L. H. Patil, D. Dalgade, and A. Hutke, "A novel clustering approach and adaptive SVM classifier for intrusion detection in WSN: A data mining concept," *Sustain. Comput., Informat. Syst.*, vol. 23, pp. 120–135, Sep. 2019.

[27] F. Javier, D. L. Calle, D. F. Garcia, and R. Usamentiaga, "Feature subset selection for support vector machines through discriminative function pruning analysis," *IEEE Trans. Syst. Man, Cybern. B, Cybern.*, vol. 34, no. 1, pp. 60–67, Feb. 2004.

[28] M. Böhland, W. Doneit, L. Gröll, R. Mikut, and M. Reischl, "Automated design process for hybrid regression modeling with a one-class SVM," *At-Automatisierungstechnik*, vol. 67, no. 10, pp. 843–852, Oct. 2019.

[29] X. Ren, Y. Wang, T. Guo, and Q. Wang, "Robust adaptive beamforming using support vector machines," *IEEE Access*, vol. 8, pp. 137955–137965, 2020.

[30] S. Todnatee and C. Phongcharoenpanich, "Iterative GA optimization scheme for synthesis of radiation pattern of linear array antenna," *Int. J. Antennas Propag.*, vol. 2016, pp. 1–8, Jun. 2016.

[31] X. Li, J. Z. Zhou, and X. L. Du, "Planar arrays synthesis for optimal wireless power transmission," *IEICE Electron. Exp.*, vol. 12, no. 11, Jun. 2015, Art. no. 20150346.

[32] A. Sharaqa and N. Dib, "Circular antenna array synthesis using firefly algorithm," *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 24, no. 2, pp. 139–146, Mar. 2014.

[33] P. Saxena and A. Kothari, "Optimal pattern synthesis of linear antenna array using grey wolf optimization algorithm," *Int. J. Antennas Propag.*, vol. 2016, pp. 1–11, Apr. 2016.

[34] H. Li, Y. Liu, G. Sun, A. Wang, and S. Liang, "Beam pattern synthesis based on improved biogeography-based optimization for reducing sidelobe level," *Comput. Elect. Eng.*, vol. 60, pp. 161–174, May 2017.

[35] Y. Li, F. Yang, J. Ouyang, and P. Yang, "Synthesis of conical conformal array antenna using invasive weed optimization method," *Appl. Comput. Electromagn. Soc. J.*, vol. 28, no. 11, pp. 1025–1030, 2013.

[36] G. Sun, Y. Liu, J. Li, Y. Zhang, and A. Wang, "Sidelobe reduction of large-scale antenna array for 5G beamforming via hierarchical cuckoo search," *Electron. Lett.*, vol. 53, no. 16, pp. 1158–1160, Aug. 2017.

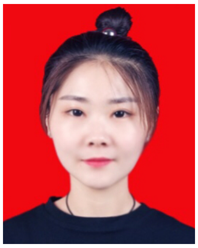
[37] G. Sun, Y. Liu, S. Liang, Z. Chen, A. Wang, Q. Ju, and Y. Zhang, "A sidelobe and energy optimization array node selection algorithm for collaborative beamforming in wireless sensor networks," *IEEE Access*, vol. 6, pp. 2515–2530, 2018.

[38] S. Deb, X.-Z. Gao, K. Tammi, K. Kalita, and P. Mahanta, "A new teaching–learning-based chicken swarm optimization algorithm," *Soft Comput.*, vol. 24, no. 7, pp. 5313–5331, Apr. 2020.

[39] S. Liang, Z. Fang, G. Sun, Y. Liu, G. Qu, and Y. Zhang, "Sidelobe reductions of antenna arrays via an improved chicken swarm optimization approach," *IEEE Access*, vol. 8, pp. 37664–37683, 2020.

[40] W. Di, M. Wang, and X. Sun, "Ldentification of bolt anchorage defects based on Elman neural network optimised by improved chicken swarm optimisation algorithm," *Insight*, vol. 62, no. 10, pp. 588–597, Oct. 2020.
[41] S. Liang, T. Feng, and G. Sun, "Sidelobe-level suppression for linear and circular antenna arrays via the cuckoo search–chicken swarm optimisation algorithm," *IET Microw., Antennas Propag.*, vol. 11, no. 2, pp. 209–218, Jan. 2017.

LIN CUI received the B.S. degree from the Inner Mongolia University of Science and Technology, Baotou, China, in 2006, and the M.S. and Ph.D. degrees from Northwestern Polytechnic University, Xi'an, China, in 2009 and 2013, respectively. She is currently a Lecturer with Xi'an Polytechnic University. Her main research interest includes array signal processing.



YIXIN ZHANG received the B.S. degree from the Zhengzhou University of Economics and Business, Zhengzhou, China, in 2018. She is currently pursuing the M.S. degree with Xi'an Polytechnic University, Xi'an, China. Her main research interest includes array signal processing.

YAMENG JIAO received the B.S. degree from the Henan Institute of Science and Technology, Luoyang, China, in 2005, and the M.S. and Ph.D. degrees from Northwestern Polytechnic University, Xi'an, China, in 2008 and 2013, respectively. She is currently a Lecturer with Xi'an Polytechnic University. Her main research interest include array signal processing.