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Abstract. With the wide application of Internet of Things (IoT) systems in the smart ocean, many unmanned surface vehicles (USVs) have been deployed jointly with unmanned aerial vehicles (UAVs) to monitor the maritime environment. However, conventional means of maritime communications fail to provide high-rate services due to the complex maritime channel conditions and large transmission distance, which will affect the environmental monitoring performance. In this paper, we propose a USV-UAV collaborative patrol scheme for maritime environment monitoring networks. Considering the characteristic of energy concentration in beamforming, we investigate the joint beamforming and location deployment optimization problem (BLDO) for UAV relay. Specifically, we decompose the BLDO problem into two subproblems. In the first sub-problem, the location deployment of UAV and beam gain allocation is optimized via an iterative algorithm based on the approximated beam patterns. The algorithm can effectively reduce the computational complexity of the grid-search method. In the second sub-problem, beamforming optimization is conducted with a high-dimensional constant-modulus (CM) constraint. A micro-particle swarm optimization-based algorithm with boundary relaxation ($BR{-}\mu PSO$) is proposed to obtain an optimal solution. Finally, the simulation results demonstrate that the proposed algorithms can improve the performance in terms of the achievable sum rate and the beam gain.

Keywords: UAV · USV · Maritime environment monitoring · Deployment · Beamforming

1 Introduction

With the rapid development of the maritime economy, oily wastewater, toxicant-containing wastewater, and domestic solid wastes, etc., pose a serious threat to ecological environment protection, which is becoming an urgent issue [1]. Yan *et al.* [2] deployed a wireless sensor network (WSN) to locate the source of pollution in the urban water supply network. However, WSN is inflexible and has limited monitoring range and unsatisfactory adaptability to the complex maritime environment. The existing maritime communication systems typically rely on satellite communications and very-high-frequency (VHF) communications [3]. However, the high cost of satellite communication and the limited bandwidth of VHF cannot support the access of multiple acquisition terminals. Therefore, it is imperative to design efficient data uploading schemes to improve the communication capacity for maritime environmental monitoring networks.

To increase the communication capacity, multiple antenna technique has been introduced for maritime communication systems in [4]. Particularly, beamforming (BF) in multiple-input multiple-output (MIMO) system has been considered as one of the major candidate technologies [6–9]. Beamforming technology provides the benefits of increased diversity for the BS and user equipment. Smart antennas enable increase of capacity in wireless communication systems by successfully reducing channel interference. Zhu *et al.* in [6] employed the analog beamforming to achieve the directional beamforming, which can effectively suppress the interference from other users. Su *et al.* in [7] demonstrated that beamforming technique can offer considerable beam gain to overcome the high propagation loss. To further improve the transmission rate, Zhu *et al.* in [6] and Xiao *et al.* in [8] explored the joint power allocation and beamforming for a two-user downlink and uplink mm-Wave NOMA scenario, respectively. At present, most of the studies are based on terrestrial communication systems.

Unmanned Aerial Vehicles (UAVs) have been widely employed in emergency and environmental monitoring tasks in the past few years. However, for the existing methods on UAV deployment monitoring[9, 10, 12], beamforming has not been taken into consideration yet. They may suffer from the interference from the maritime climate and neighboring infrastructures [10]. Considering the flexibility of UAVs and the advantages of beamforming technology such as anti-interference and energy concentration, the combination of the two is very promising [11, 12]. It can not only improve the communication quality of UAV, but also save communication energy consumption. However, the joint beamforming and UAV location optimization problem will be more complicated since it is highly non-convex and involves high-dimensional, highly coupled variable vectors. For example, Mozaffari *et al.* in [12] presented a grid-search method to calculate the maximum achievable rate of each grid intersection point to determine the approximate optimal location of the UAV. Whereas the algorithm complexity increases exponentially making it difficult to determine the optimal grid accuracy.

The aforementioned beamforming schemes are suitable for terrestrial systems, yet few contributions have been devoted to the problem of maritime beamforming systems. When designing the UAV-assisted USV patrol scheme, the following differences between ocean and land have to be investigated :

- Channel distinction: Maritime propagation environment has unique characteristics such as sparsity, instability and the ducting effect over the sea surface. Therefore, we need to establish a multipath channel model suitable for the characteristics of the maritime environment.

• Energy limitation: The offshore relays are usually powered by solar energy due to the lack of infrastructure. Therefore, we should reduce communication energy consumption as much as possible.

In order to meet the aforementioned challenges, we investigate the beamforming and location deployment optimization (BLDO) problem for UAV-assisted maritime environment monitoring networks. Specifically, the energy is concentrated in the target USV direction through beamforming technology. Since the variables are coupled with each other and have high dimensions, the BLDO problem is decomposed into two sub-problems by introducing the ideal beamforming. In the first stage, an iterative algorithm based on water injection is proposed to find the UAV's optimal position. In the second stage, considering the difficulty of the constant modulus (CM) constraint and the "curse of dimensionality" of the high-dimensional problems, a micro-particle swarm algorithm ($BR - \mu PSO$) is proposed based on boundary relaxation to obtain the beamforming vector. Our main contributions are summarized as follows:

• Beamforming technology is combined with UAV assisted communication to maximize the achievable sum rate of data uploading from the patrol USVs. The beam gain of the target USV direction is significantly enhanced, thus solving the problem of limited maritime communication bandwidth without increasing hardware cost.

• An iterative algorithm and a particle swarm optimization algorithm based on boundary relaxation ($BR - \mu PSO$) are proposed to solve the UAV location deployment and beamforming optimization problems, respectively. The results show that, the energy is concentrated in the direction of target USVs, and the proposed algorithms can efficiently improve the achievable sum rate and the beam gain.

The rest of this paper is organized as follows. The system and channel model of the maritime MIMO system is introduced in Section II. Sections III and IV describe the deployment and analog beamforming optimization of the hovering UAV, respectively. The simulation results are presented and discussed in Section V. Section VI concludes this paper.

Notation: In this paper, $\mathbf{I}_n$ stands for an $n \times n$ identity matrix, $()^H$, $||$, $\|\|$ denote Hermitian transpose, the absolute value of a complex number, the Euclidean norm respectively.

2 System Model and Problem Formulation

2.1 System Model

We consider a UAV-assisted USV patrol scheme for maritime monitoring network as depicted in Fig. 1, where one UAV is responsible for air patrol and the USVs are responsible for information collection. The network is expected to realize high reliability and low delay in information transmission while increasing communication capacity. The UAV is equipped with an M-element uniform linear array (ULA), serving K USVs with a single antenna. To enable multistream communications, each antenna branch has a phase shifter and a power amplifier (PA) to drive the antenna.

For the sake of convenience, we establish a 3-D rectangular coordinate system to represent UAV and USVs' location relationship, where USVs are distributed on the horizontal plane located at $(x_k, y_k, 0)$ and the coordinate of the UAV is (x_u, y_u, h_u). Note that we use orthogonal frequency division multiplexing (OFDM) technology, where each USV occupies an independent frequency to transmit the information $s_k \sim \mathcal{CN}(0, 1)$ to the UAV relay. The kth USV transmits signal s_i to the UAV with the corresponding transmit power p_k, where $\mathbb{E}(|s_i|^2) = 1$. Then the received signal $\mathbf{y}_{UAV} \in \mathbb{C}^{M \times 1}$ at the UAV can be expressed as

$$\mathbf{y}_{UAV} = \sum_{k=1}^{K} \mathbf{H}_k^H \mathbf{w} \sqrt{p_k} s_k + \mathbf{n_1} \tag{1}$$

where $\mathbf{H}_k$ is channel response vector between the k**th** USV and the UAV, the elements of vector $\mathbf{n_1}$ represent additive white Gaussian noise (AWGN) with variance σ_1^2, and $\mathbf{w}$ denotes an $M \times 1$ beamforming (BF) vector with CM constraint for ULA structure, i.e., $|[\mathbf{w}_k]| = \frac{1}{\sqrt{M}}$ for $k = 1, 2, \ldots, M$.

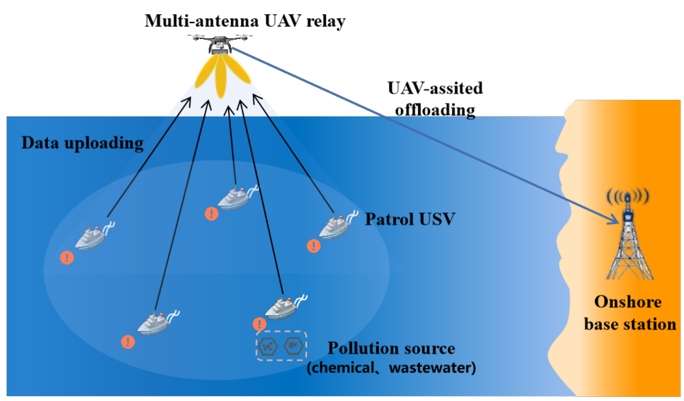

Fig. 1: Illustration of a maritime patrol scenario including one UAV, and multiple USVs.

Due to the lack of scatters in the vast sea area, the line-of-sight (LoS) path will dominate most of the air-to-sea channels. The Rayleigh fading, generally analyzed in the terrestrial communication systems, may no longer be suitable for the maritime environment. Instead, the finite scattering channel [13] could be more appropriate for the maritime model. Furthermore, the reflection path from the sea surface may exist in some conditions, resulting in severe multipath effects. Therefore, a sparse multipath channel based on multipath fading is conceived to describe the USV-UAV channel in our model. The uplink channel (UL) between USV and UAV is denoted by $\mathbf{h}_k$. Different multipath components (MPCs) have different physical receive steering angles, i.e., angles of arrival (AoAs). With half-spaced ULAs adopted at the receiver, the channel matrix can be expressed as

$$\mathbf{a}_r\left(\phi_l\right)=\sqrt{\frac{1}{M}}\left[1,e^{j\pi\phi},\cdots,e^{j\pi(M-1)\phi}\right]^T \tag{2}$$

$$\phi_l=\frac{x_u-x_i}{\sqrt{\left(x_u-x_k\right)^2+\left(y_u-y_k\right)^2+h_u^2}} \tag{3}$$

$\mathbf{a}_r\left(\phi_l\right)$ is the antenna array response vector at the UAV, where ϕ_l denotes the real AoA of the lth MPC for the kth USV i.e. $\phi_l = cos\left(AoA\right)$, and ϕ_l is within the range of $(-1,1)$. We only consider the azimuth and neglect elevation to implement horizontal 2-D beamforming. The extension to 3-D beamforming by adopting an uniform planar array (UPA) configuration may also be possible.

2.2 Problem Formulation

In this subsection, we aim to maximize the achievable sum uploading rate of all USVs when the channel is known prior. For each USV, under the constraints of minimal rate for USVs and antenna structure, the achievable rate R_k is denoted by

$$R_k=\log_2\left(1+\frac{p_k\left|\mathbf{h}_k^H\mathbf{w}\right|^2}{\sigma^2}\right) \tag{4}$$

where p_k is the transmission power at each USV, and σ^2 is the power of Gaussian white noise at ith USV. $\left|\mathbf{h}_k^H\mathbf{w}\right|^2$ denotes the effective channel gain between the kth USV and UAV. In this problem, the UAV deployment intertwines with the beamforming design, accordingly, the achievable sum rate maximization problem can be formulated as

$$\begin{aligned}
&P_0:\max_{\mathbf{w},x_u,y_u}\sum_{k=1}^{K}\log_2\left(1+\frac{p_k\left|\mathbf{h}_k^H\mathbf{w}\right|^2}{\sigma^2}\right)\\
&\text{s.t. C1}:R_k\geq\zeta_k \qquad k=1,2\ldots,K\\
&\qquad \text{C2}:\left|[\mathbf{w}]_i\right|=\frac{1}{\sqrt{M}} \qquad i=1,2\ldots,N\\
&\qquad \text{C3}:(x_u,y_u)\in\mathbb{D}
\end{aligned} \tag{5}$$

where ζ_k denotes the minimum rate requirement for kth USV, and thus, C1 denotes the QoS requirement for each USV. Meanwhile, $|[\mathbf{w}]|=\frac{1}{\sqrt{M}}$ is the CM constraint due to usig the phase shifters in each antenna branch at the UAV. The optimization variables are the projected coordinates of UAV (x_u,y_u) and the beamforming vector $\mathbf{w}$.

3 Problem Solution

Directly solving the BLDO problem (5) by using the existing optimization tools is infeasible, because the problem is non-convex, and the UAV position variables intertwine with the beamforming vector. Since the location of the UAV crucially affects the channel matrix, we can resort to the approximate beam pattern and decompose the BLDO problem into two sub-problems that are relatively easy to solve one by one.

3.1 UAV Deployment and Beam Gain Allocation Sub-Problem

We first resort to approximate beam patterns and try to decompose the deployment and beamforming variables. Then, we have the following lemma.

Lemma 1: With the ideal beamforming, the beam gains satisfy

$$\frac{\delta_1}{\left|\bar{\lambda}_1\right|^2}+\frac{\delta_2}{\left|\bar{\lambda}_2\right|^2}+\cdots+\frac{\delta_k}{\left|\bar{\lambda}_k\right|^2}=M \tag{6}$$

Note that in the case of ideal beamforming, the beam gains along the USV directions are fixed with a beam width of $\frac{K}{M}$, while those along nonuser directions are all zeros, i.e., there are no side lobes. Then, we have $\sum_{k=1}^{K}\frac{\left|\mathbf{h}_k^H\mathbf{w}\right|^2}{\left|\bar{\lambda}_k\right|^2}=M$, where $\delta_k{=}\left|\mathbf{a}_k^H\mathbf{w}\right|^2$ denotes the antenna beam gain of the kth USV, and $\left|\bar{\lambda}_k\right|=\max\left|\lambda_{m,l}^k\right|$, denotes the index of the strongest MPC for USVs. For the kth USV, the UAV maximizes the effective channel gain by fixed beam direction. It can be approximated as

$$\left|\mathbf{h}_k^H\mathbf{w}\right|^2\approx\left|\bar{\lambda}_k\right|^2\left|\mathbf{a}_k^H\mathbf{w}\right|^2 \tag{7}$$

Therefore, based on Lemma 1, we can rewrite the original achievable sum rate maximization problem with the beamforming gains, and simplify it to the problems of UAV deployment and beam gain assignment.

$$\begin{aligned}
P_1:&\max_{(x_u,y_u),\delta_k}\sum_{k=1}^{K}\log_2\left(1+\frac{\sum\limits_{m=1}^{M}p_m^k\left|\bar{\lambda}_k\right|^2\delta_k}{\sigma^2}\right)\\
\text{s.t. } &\text{C1}:\log_2\left(1+\frac{\sum\limits_{m=1}^{M}p_m^k\left|\bar{\lambda}_k\right|^2\delta_k}{\sigma^2}\right)\geq\zeta_{m,k}\qquad k=1,2\dots,K\\
&\text{C2}:\sum_{k=1}^{K}\frac{\delta_k}{\left|\bar{\lambda}_k\right|^2}=M\\
&\text{C3}:(x_u,y_u)\in\mathbb{D}\qquad r_i\in\mathcal{R}
\end{aligned} \tag{8}$$

We impose a threshold ζ_m^k on the $SINR_m^k$ for reliable decoding(i.e., $SINR_m^k \geq \zeta_m^k$). C2 is the constraint on ideal beamforming. At the same time, the CM constraint can be ignored in the first sub-problem.

The details of the proposed algorithm are presented in **Algorithm 1**.

Algorithm 1 UAV Position Optimization and Beam Gain Allocation

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1: **Initialize** $\left(x^{(0)}, y^{(0)}\right)$ and $\delta_i^{(0)} = \frac{M}{K}$, set $n = 1$ as the initial feasible point
2: **Repeat**
3: With given $\left(x^{(n-1)}, y^{(n-1)}\right)$ and $\delta_i = \delta_i^{(n-1)}$, calculate $F^{(n-1)}\left(x_u, y_u, \delta_i\right)$
4: Calculate $x^{(n)} = \arg\max F\left(y^{(n-1)}, \delta_i^{(n-1)}\right)$
5: Calculate $y^{(n)} = \arg\max F\left(x^{(n)}, \delta_i^{(n-1)}\right)$
6: Solve $F\left(\delta_i^{(n)}\right)$ using water filling algorithm
7: Calculate $F^{(n)} = F\left(x^{(n)}, y^{(n)}, \delta_i^{(n)}\right)$
8: Update $n = n+1$, $y_u = y^{(n-1)}$, $x_u = x^{(n-1)}$
9: **Until** $\left|F^{(n)} - F^{(n-1)}\right| \leq \varepsilon$
10: **Output** $\left(x_u^*, y_u^*, \delta_i^*\right)$ as the optimal solution

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We have hereto solved the first subproblem, and obtain an optimal location of the UAV under the assumption of approximate beamforming.

3.2 Beamforming Optimization Sub-Problem

Substituting the obtained optimal location of UAV to the BLDO problem, we obtain the beamforming sub-problem. Since the analog beamforming should support all of the patrol USVs, the principle of beamforming design is to maximize the array gains for all USVs. However, the CM constraint is not accounted for in P_1, and we consider it in the following beamforming sub-problem P_2:

$$\begin{aligned} P_2 : &\max_{\mathbf{w}} \sum_{k=1}^{K} \left|\mathbf{h}_k^H \mathbf{w}\right|^2 \\ \text{s.t. } &\text{C1} : \log_2\left(1 + c_k \cdot \left|\mathbf{a}_k^H \mathbf{w}\right|^2\right) \geq \xi_k \qquad k = 1, 2 \ldots, K \\ &\text{C2} : \sum_{k=1}^{K} \frac{\delta_k}{\left|\bar{\lambda}_k\right|^2} = M \qquad i = 1, 2 \ldots, M \\ &\text{C3} : \left|[\mathbf{w}]_m\right| = \frac{1}{\sqrt{M}} \end{aligned} \tag{9}$$

where $c_k = \left(\frac{P \cdot \left|\bar{\lambda}_k\right|^2}{\delta^2}\right)$ is the channel gain coefficient along the strongest MPC. Problem P_2 is clearly non-convex. In order to ensure that the modulus value of each element in $\mathbf{w}$ is $1\Big/\sqrt{M}$, we transform it into angle domain, and then optimize its phase. It has been confirmed that the phase rotation of the BF does not affect the optimality of this problem. Let $\mathbf{w} = \left(1\Big/\sqrt{M}\right) \cdot e^{j\boldsymbol{\varphi}}$, then we have $\left|\mathbf{h}_k^H \mathbf{w}\right|^2 = \left|\lambda_k\right|^2 \cdot \frac{1}{M}\left|\mathbf{a}_k^H e^{j\boldsymbol{\varphi}}\right|^2$.

It has been confirmed that the phase rotation of the BF does not affect the optimality of this problem. Therefore, the elimination norm operation can be performed, and $\mathbf{a}_k^H e^{j\boldsymbol{\varphi}}$ is real and non-negative. We proposed a suboptimal solution, meanwhile, we will provide the optimal solution by relaxing P_2 into the following convex problem:

$$\begin{aligned} & P_3 : \max_{\boldsymbol{\varphi}} \sum_{k=1}^{K} \mathbf{a}_k^H e^{j\boldsymbol{\varphi}} \\ & \text{s.t. C1} : \log_2\left(1 + c_k \cdot \left|\mathbf{a}_k^H e^{j\boldsymbol{\varphi}}\right|^2\right) \geq \xi_k \qquad k = 1, 2 \ldots, K \\ & \qquad \text{C2} : \sum_{k=1}^{K} \frac{\delta_k}{\left|\bar{\lambda}_k\right|^2} = M \qquad i = 1, 2 \ldots, M \\ & \qquad \text{C3} : \mathrm{Im}(\mathbf{a}_k^H e^{j\boldsymbol{\varphi}}) = 0 \end{aligned} \tag{10}$$

To solve this problem, some swarm-based algorithms can be considered here, e.g., particle swarm optimization (PSO) algorithm. However, the performance of PSO algorithm begins to decline for high-dimensional problems. In this paper, a micro-particle swarm algorithm with boundary relaxation ($BR - \mu PSO$) is proposed. We transform P_3 into an unconstrained one by means of the penalty function, so we redescribe the constraint of C1 as

$$g_i\left(\boldsymbol{\varphi}\right) = \log_2\left(1 + c_k \cdot \frac{1}{M}\left|\mathbf{a}_k^H e^{j\boldsymbol{\varphi}}\right|^2\right) - \xi_k \geq 0 \tag{11}$$

The objective function can be rewritten as:

$$\begin{aligned} & P_4 : \underset{\boldsymbol{\varphi}}{\text{Minimize}} - \sum_{k=1}^{K} \mathbf{a}_k^H e^{j\boldsymbol{\varphi}} + \mu \sum_{i=1}^{K} \left[\max\left\{0, -g_i\left(\boldsymbol{\varphi}\right)\right\}\right]^2 \\ & \text{s.t. C1} : \sum_{k=1}^{K} \frac{\delta_k}{\left|\bar{\lambda}_k\right|^2} = M \qquad i = 1, 2 \ldots, M \\ & \qquad \text{C2} : \mathrm{Im}(\mathbf{a}_k^H e^{j\boldsymbol{\varphi}}) = 0 \end{aligned} \tag{12}$$

where the penalty function is expressed as

$$\max\left\{0, -g_i\left(\boldsymbol{\varphi}\right)\right\} = \begin{cases} 0 \\ -g_i\left(\varphi\right) \end{cases} \tag{13}$$

If $\boldsymbol{\varphi}$ is a feasible solution, the value is 0. If not, the value is $-g_i\left(\boldsymbol{\varphi}\right)$. Each particle has a memory for its best found position $\mathbf{P}_{best}$ and the globally best position

$\mathbf{G}_{best}$. The rate update formula of $\mathbf{G}_{best}$:

$$[\mathbf{V}]_{g,n}^{t+1} = \omega\,[\mathbf{V}]_{g,n}^{t} - [\mathbf{X}]_{g,n}^{t} + [\mathbf{G}_{best}]_n + [\mathbf{rep}]_{g,n}^{t} \tag{14}$$

For each iteration, the velocity and position of each particle are updated based on:

$$\begin{aligned}[\mathbf{V}]_{j,n}^{t+1} &= \omega\,[\mathbf{V}]_{j,n}^{t} + \mathrm{rand}() * ([\mathbf{P}_{best}]_{j,n} - [\mathbf{X}]_{j,n}^{t}) \\ &+ \mathrm{rand}() * ([\mathbf{G}_{best}]_n - [\mathbf{X}]_{j,n}^{t}) + [\mathbf{rep}]_{j,n}^{t}\end{aligned} \tag{15}$$

$$[\mathbf{X}]_{j,n}^{t+1} = \begin{cases} [\mathbf{X}]_{j,n}^{t} + [\mathbf{V}]_{g,n}^{t+1}, & [\mathbf{X}]_{j,n}^{t} = [\mathbf{X}]_{g,n}^{t} \\ [\mathbf{X}]_{j,n}^{t} + [\mathbf{V}]_{j,n}^{t+1}, & \text{else} \end{cases} \tag{16}$$

The parameter ω is the inertia weight of velocity. $[\mathbf{rep}]_{i,n}^{t}$ is the repulsion experienced from K blacklisted solutions. $\mathbf{d}_{ki} = \mathbf{x}_i - \hat{\mathbf{x}}_k$ is a vector pointing from the blacklisted solution l to the ith particle. The details of the proposed $BR-\mu PSO$ algorithm are presented in **Algorithm 2**.

Due to the equality constraint, the search space for $\mathbf{X}$ is high-dimensional. We relax the search space to a convex set and adjust the particles on the boundaries of each iteration. The outer and inter boundary is defined as

$$\left\{\mathbf{X} \middle| \left|[\mathbf{X}]_{i,j}\right| = d_{beyond}\right\} \quad d_{beyond} = \frac{1}{\sqrt{M}} \tag{17}$$

$$\left\{\mathbf{X} \middle| \left|[\mathbf{X}]_{i,j}\right| = d_{in}\right\} \quad d_{in} = \frac{t}{T_{\max}} \frac{1}{\sqrt{M}} \tag{18}$$

For each iteration, the particles out of the boundary are adjusted onto the boundary, and eventually converge.

4 Simulation Results

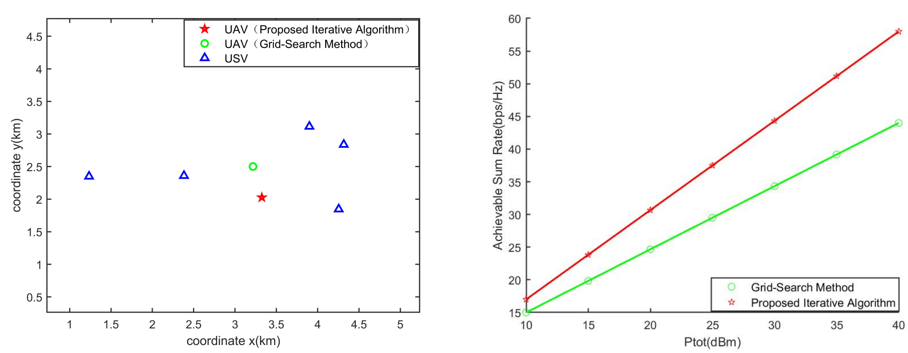
In this section, simulation results are presented to demonstrate the performance of our proposed iterative algorithm for UAV deployment and the $BR-\mu PSO$ algorithm for beamforming optimization. We consider a scenario that one UAV serves multiple patrol USVs. In the simulation experiment, the positions of USVs are randomly generated. Then we set $p_k = 35dBm$, $\sigma^2 = -100dBm$ and $h_u = 200m$, which are some typical parameters of offshore area [8].

First, we evaluate the performance of the proposed UAV deployment approach. Fig. 2 compares the random beam pattern with the designed beam pattern by solving problem P_1, where we assume the minimum rate constraints for each USVs are 1, 4, 4, 3 and 3 bps/Hz, respectively. It shows the uplink achievable sum rate and the optimal UAV position comparison between the proposed iterative algorithm and the grid-search method in the scenario of five USVs. Fig. 2 (a) shows a 2D scatter plot of the USV-UAV deployment relationship, which is affected by USVs minimum rate constraints. It can be seen in Fig. 2 (b) that the proposed iterative algorithm has better performance in terms of

Algorithm 2 Implementation of $BR - \mu PSO$

Input:
The number of antennas M
The number of particle swarm I
Maximum number of the iterations T
The range of inertia weight $\omega_{\min}$ and $\omega_{\max}$
Output: φ^{opt}

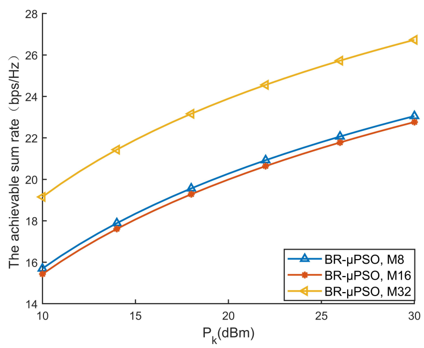
Initialize the position $\mathbf{x}_i = \boldsymbol{\varphi}_i$ and velocity $\mathbf{v}_i$
Obtain the $\mathbf{rep}_i$, d_{beyond} and d_{in} according to (17)(18)(19)
while $t \leq T$ **do**
  Obtain the fitness function $F_t(\mathbf{X})$ according to (12)
  for $i = 1 : I$ **do**
    for $n = 1 : M$ **do**
      Update $[\mathbf{X}]_{j,n}^{t+1}$ and $[\mathbf{V}]_{j,n}^{t+1}$ according to (15) (16)
      if $\left|[\mathbf{X}]_{i,j}\right| > d_{beyond}$ **then**
        $\mathbf{X}_{i,j} = d_{beyond} \frac{[\mathbf{X}]_{i,j}}{\left|[\mathbf{X}]_{i,j}\right|}$
      end if
      if $\left|[\mathbf{X}]_{i,j}\right| < d_{in}$ **then**
        $\mathbf{X}_{i,j} = d_{in} \frac{[\mathbf{X}]_{i,j}}{\left|[\mathbf{X}]_{i,j}\right|}$
      end if
      if $\left|[\mathbf{p}_{best}]_{i,j}\right| < d_{in}$ **then**
        $[\mathbf{p}_{best}]_{i,j} = d_{in} \frac{[\mathbf{p}_{best}]_{i,j}}{\left|[\mathbf{p}_{best}]_{i,j}\right|}$
      end if
    end for
    Update $\mathbf{p}_{best}$
  end for
  Update $\mathbf{g}_{best}$
  if $(F_{t+1}(\mathbf{X}^*) < F_t(\mathbf{X}^*))$ **then**
    $\mathbf{T}[:, i] = [\mathbf{X}^*]^{t+1}$
    $\omega = \min(\omega_{\min}(1+\beta), \omega_{\max})$
  else
    Reset $\omega = \omega_{\min}$
  end if
  Reset $\mathbf{g}_{best}$ and $\mathbf{p}_{best}$ location and velocity matrices
  $t = t + 1$
end while
$\varphi^{opt} = \mathbf{g}_{best}$
return φ^{opt}



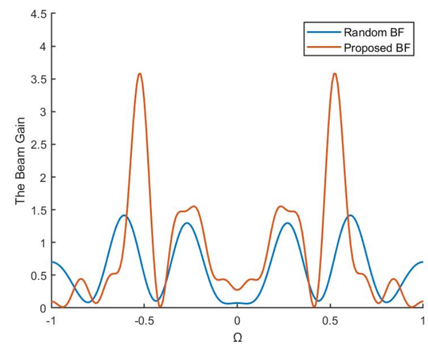
(a) UAV location deployment. (b) The achievable sum rate via P_k.

Fig. 2: Location and performance of UAV deployments.

the achievable sum rate than the grid-search method. Then, we evaluate the performance of the proposed beamforming algorithm. The beamforming vector $\mathbf{w}$ is designed to approach the approximate beam gain of each USV. Fig. 3 (a) shows the comparison between the achievable sum rate via the proposed beam pattern with different numbers of antennas against P_k, $M = 8, 16, 32$ and $K = 2$. Fig. 3 (b) shows the beam gain comparison result between the random and proposed beamforming. We can observe that the proposed beamforming pattern is effective, and the beam gains are concentrated on the target USVs' directions.



(a) The achievable sum rate via P_k.



(b) The beam gain with different numbers of antennas.

Fig. 3: The achievable sum rate gain and beam gain of the proposed beam patterns.

5 Conclusion

This paper has investigated the joint beamforming and location deployment optimization problem (BLDO) for UAV relay, aiming to maximize the uplink achievable sum rate of the USV-UAV collaborative patrol scheme for maritime monitoring network. The original formulated BLDO problem has been decomposed into two sub-problems by the approximate beam pattern. The subproblem of deployment and beam gain allocation sub-problem has been first solved via the proposed alternating optimization. Then, the beamforming sub-problem has been tackled by the proposed $BR - \mu PSO$ algorithm. Simulation results have shown that the proposed scheme could effectively increase the performance of the achievable sum rate and beam gain in the USVs direction. For future work, we will investigate the effect of the unstable beam pointing problem.

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