Optimizing UAV Deployment for Enhanced Detection Performance in Multi-UAV Cooperative Sensing

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***Abstract*—In this work, we enhance cooperative sensing capabilities in multi Unmanned Aerial Vehicles (UAVs) systems, with each UAV mounted with a directional antenna to detect multiple targets cooperatively. To improve detection accuracy in dynamic environments with noise fluctuations, we adopt an eigenvalue-based detection technique. We maximize total detection probability by simultaneously optimizing the spatial deployment of UAVs and their antenna orientations. To address the inherent non-convexity of this problem, we propose an iterative Particle Swarm Optimization (PSO)-based approach with a penalty method for its fitness function. The proposed approach effectively navigates complex search spaces, managing spatial and antenna constraints to guide solutions toward global optima. Monte Carlo simulations demonstrate that our PSO-based algorithm outperforms current techniques, achieving superior detection performance and robust sensing capabilities. Notably, the proposed scheme achieves a 7.94% improvement with 2 UAVs and a 7.21% improvement with 3 UAVs over the alternating direction penalty method (ADPM)-based scheme, highlighting its effectiveness even with fewer UAVs deployed for cooperative sensing.**

***Index Terms*—Unmanned Aerial Vehicles, Eigenvalue-Based Detection, Particle Swarm Optimization, Cooperative Sensing.**

I. Introduction

The usage of multi-UAVs-based systems has integrated into various fields, ranging from civilian to commercial applications, with significant use in the military [1], [2]. Among these, the use of multi-UAVs for spectrum sensing is gaining popularity for its maneuverability, flexible deployment, and ability to maintain Line-of-Sight (LoS) communication. As a result, cooperative sensing with multi-UAV systems has emerged as a powerful approach to enhance detection capabilities across large areas, especially where traditional sensing schemes face limitations [3], [4].

In recent years, many studies have sought to improve energy detection for sensing systems due to its simplicity and low computational cost [5]–[7]. In [8], authors proposed crowd-sourced sensing using distributed sensors, while in [9], 3D RF sensor networks are examined for spectrum monitoring. In [10] authors analyzed spectrum characteristics at large spatio-temporal scales, emphasizing the need for adaptive monitoring. In [11], authors introduced resource coordination strategies for reliable detection in multi-UAV networks.

However, energy detection depends on accurate knowledge of noise power. Inaccurate estimation of noise power can result in a high probability of false alarms and a signal-to-noise ratio (SNR) wall, making this method highly sensitive to noise fluctuations [12], [13]. This sensitivity leads to performance degradation in UAV-based applications, where dynamic and unpredictable conditions lead to frequent noise variations, especially in low SNR environments.

To overcome the limitations of energy detection identified in prior work [11], we adopt an eigenvalue-based detection (EBD) technique to enhance sensing performance and remains robust under varying noise conditions. Unlike energy detection, EBD does not rely on prior knowledge of noise variance, making it particularly effective under noise uncertainty—an essential advantage for UAV sensing applications [14], [15]. By jointly optimizing UAV deployment and directional antenna configurations, our method ensures better resource coordination to achieve maximum detection probability.

We address the challenge of maximizing sum detection probability through joint optimization of UAV positions and antenna settings, tackling a non-convex problem with spatial and orientation constraints. To solve this, we propose an iterative PSO-based algorithm, that explores complex search spaces through heuristic exploration and exploitation [16]. Each UAV's position and antenna setting represented by particles, are optimized to enhance detection performance. To ensure practical deployment, we incorporate a penalty-based approach within the PSO fitness function to penalize configurations that violate spatial, distance, or orientation constraints, enabling efficient UAVs deployment even under strict conditions [17].

The main contributions of this paper are as follows:

- We propose an optimization framework for multi-UAV cooperative sensing using eigenvalue-based detection, jointly optimizing UAV deployment and antenna orientation to maximize sum detection probability.

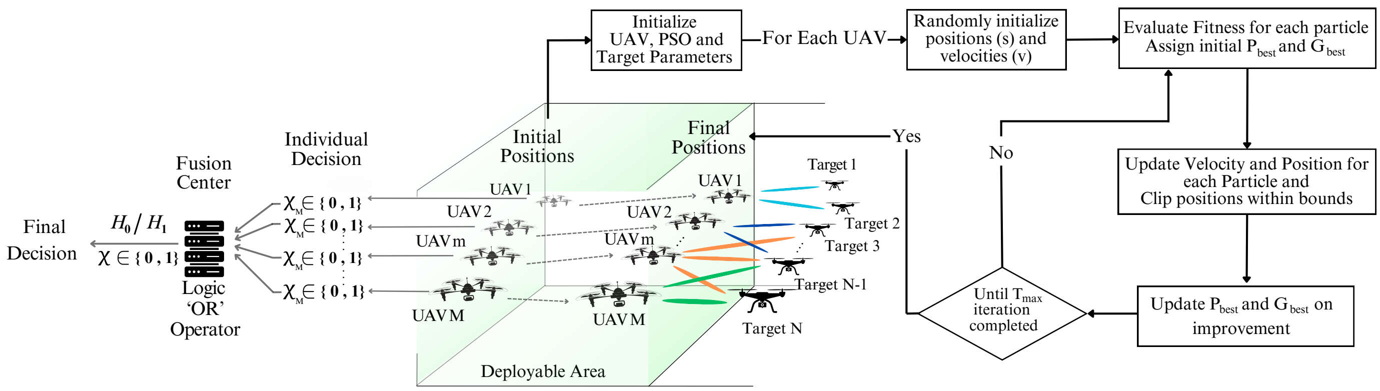

Fig. 1. Multi-UAVs sensing network, where M UAVs cooperate to detect K targets using eigenvalue-based detection along with flowchart of the proposed algorithm.

- We introduce an iterative PSO-based algorithm with a penalty method that effectively tackles the non-convex optimization problem by leveraging the ability of PSO to explore complex search spaces while applying practical constraints.
- Through Monte Carlo simulations, we demonstrate that the proposed PSO-based approach, combined with eigenvalue-based detection, outperforms traditional energy detection methods, especially in scenarios with low target transmission power and with fewer UAVs.

II. System Model

As illustrated in Fig. 1, we consider a multi-UAV spectrum sensing network where UAVs equipped with directional antennas perform eigenvalue-based detection under strict constraints. The setup uses a 3-D Cartesian coordinate system with M UAVs, represented by $m \in \{1, \ldots, M\}$, and N targets, represented by $n \in \{1, \ldots, N\}$. To minimize the energy requirement, we assume that each UAV ascends to a fixed height H to avoid obstacles and maintain this height throughout the deployment. The locations of the M UAVs are represented by $\mathbf{P} = [\mathbf{p}_1, \ldots, \mathbf{p}_M]^T \in \mathbb{R}^{M \times 3}$, where $\mathbf{p}_m = [x_m, y_m, H]^T$ defines the coordinates of the m^{th} UAV. Similarly, $\mathbf{P}'$ represents the locations of the N targets, where $\mathbf{p'}_n = [x'_n, y'_n, z'_n]^T$ specifies the coordinates of the n^{th} target.

A. Eigenvalue-Based Detection

According to [14], EBD uses the relative distribution of eigenvalues in the sample covariance matrix at each UAV, allowing it to detect signals based on statistical variations rather than absolute noise power. This technique can be formulated as a binary hypothesis testing problem, where H_0 denotes signal absence, and H_1 its presence. The received signal vector $\mathbf{y}(k) \in \mathbb{C}^{L \times 1}$ under these hypotheses is expressed as,

$$\begin{cases} H_0: & \mathbf{y}(k) = \mathbf{w}(k), \qquad k = 0, 1, \ldots, K-1, \\ H_1: & \mathbf{y}(k) = \mathbf{x}(k) + \mathbf{w}(k), \quad k = 0, 1, \ldots, K-1, \end{cases} \tag{1}$$

where $\mathbf{x}(k) \in \mathbb{C}^{L \times 1}$ is the signal component with covariance $\mathbb{E}[\mathbf{x}(k)\mathbf{x}^H(k)] = \sigma_s^2 \mathbf{I}$, and $\mathbf{w}(k) \in \mathbb{C}^{L \times 1}$ is zero-mean Additive White Gaussian Noise (AWGN) with covariance $\mathbb{E}[\mathbf{w}(k)\mathbf{w}^H(k)] = \sigma_n^2 \mathbf{I}$. Here, K is the number of samples, L is the number of sensors on each UAV, and $\mathbf{I}$ is the identity matrix. The sample covariance matrix $\mathbf{R}_y$ of the received signal is computed as:

$$\mathbf{R}_y = \frac{1}{K} \sum_{k=0}^{K-1} \mathbf{y}(k)\mathbf{y}^H(k), \tag{2}$$

where $\mathbf{y}^H(k)$ is the Hermitian transpose of $\mathbf{y}(k)$. Under H_0, $\mathbf{R}_y$ represents only the noise covariance $\sigma_n^2 \mathbf{I}$, while under H_1, it represents both the signal and noise covariances, $\sigma_s^2 \mathbf{I} + \sigma_n^2 \mathbf{I}$.

The eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L$ of $\mathbf{R}_y$ define the test statistic as $T = \frac{\lambda_1}{\lambda_L}$. And the decision rule for T is given by:

$$T \begin{cases} \geq \lambda_{EBD}, & H_1 \text{ (Signal Present)}, \\ < \lambda_{EBD}, & H_0 \text{ (Signal Absent)}, \end{cases} \tag{3}$$

where λ_{EBD} is the detection threshold. Under the null hypothesis H_0, λ_1 and λ_L follow the Tracy-Widom distribution, but for large $K \gg L$, T is approximately Gaussian under both hypotheses, where $\text{SNR} = \frac{\sigma_s^2}{\sigma_n^2}$:

$$\begin{cases} H_0: & T \sim \mathcal{N}\left(1, \frac{2}{K}\right), \\ H_1: & T \sim \mathcal{N}\left(1 + \text{SNR}, \frac{2(1+\text{SNR})^2}{K}\right), \end{cases} \tag{4}$$

The probability of false alarm P_{fa} (deciding H_1 under H_0),

$$P_{fa} = Q\left(\frac{\lambda_{EBD} - 1}{\sqrt{2/K}}\right), \tag{5}$$

where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2/2} dt$ represents the tail probability of the standard normal distribution.

The probability of detection P_d (deciding H_1 under H_1) is:

$$P_d = Q\left(\frac{\lambda_{EBD} - (1 + \text{SNR})}{\sqrt{\frac{2(1+\text{SNR})^2}{K}}}\right). \tag{6}$$

The detection threshold λ_{EBD} is chosen based on the desired false alarm probability (P_{fa}):

$$\lambda_{EBD} = 1 + \sqrt{\frac{2}{K}} Q^{-1}(P_{fa}). \tag{7}$$

By substituting this λ_{EBD} back into the equation for P_d, the probability of detection becomes:

$$P_d = Q\left(\frac{Q^{-1}(P_{fa}) - \text{SNR}\cdot\sqrt{K/2}}{(1+\text{SNR})}\right). \tag{8}$$

B. Directional Antenna Model

In multi-UAV cooperative sensing, each UAV is equipped with a directional antenna that enhances signal strength by focusing energy in a specific direction, thereby minimizing interference from other directions. This focused beam improves sensing performance by concentrating transmitted or received signals along the main lobe where the gain is substantially higher compared to other directions.

According to [18], for modeling, the antenna's gain is assumed to be constant within the main lobe's angle range, $(-\alpha, \alpha)$, and negligible outside this range. The directional gain $G_{m,n}$ between UAV m and target n can be expressed as

$$G_{m,n} = \begin{cases} \Psi_{m,n}(\eta_m), & \text{if } (\eta_{m,n} - \eta_m),\ \zeta_{m,n} \in (-\alpha, \alpha), \\ 0, & \text{otherwise,} \end{cases} \tag{9}$$

where $\Psi_{m,n}(\eta_m) = 10\log_{10}\left(\exp\left(-\frac{(\eta_{m,n}-\eta_m)^2+\zeta_{m,n}^2}{2\alpha^2}\right)\right)$. Here, $\eta_{m,n} = \arctan\left(\frac{y'_n - y_m}{x'_n - x_m}\right)$ represents the azimuth angle, and $\zeta_{m,n} = \arctan\left(\frac{z'_n - H}{\sqrt{(y'_n-y_m)^2+(x'_n-x_m)^2}}\right)$ represents the elevation angle from UAV m to target n. The term η_m represents the azimuth orientation of the directional antenna.

In air-to-air scenarios, the wireless channels between UAVs and targets are typically dominated by Line-of-Sight (LoS) links, especially when UAVs fly at moderate altitudes. As a result, we model these LoS links using a free-space channel model. Consequently, the channel power gain from UAV m to target n is defined as,

$$g_{m,n}(\mathbf{p}_m, \eta_m) = \frac{\beta_0 N_t G_{m,n}(\mathbf{p}_m, \eta_m)}{d_{m,n}^2(\mathbf{p}_m)}, \tag{10}$$

where β_0 is the reference channel gain, N_t is the number of antenna elements, and $d_{m,n}(\mathbf{p}_m)$ is the distance between UAV m and target n.

The signal-to-interference-plus-noise ratio (SINR) received by UAV m from target n with transmit power P_n is given by

$$\gamma_{m,n}(\mathbf{p}_m, \eta_m) = \frac{P_n \beta_0 N_t G_{m,n}(\mathbf{p}_m, \eta_m)}{d_{m,n}^2(\mathbf{p}_m)\sigma_n^2}, \tag{11}$$

where σ_n^2 is the power of AWGN at the receiver. And by substituting SNR with the $\gamma_{m,n}$ in (9),we get the probability of detection by UAV m for target n expressed as:

$$P_{m,n}(\mathbf{p}_m, \eta_m) = Q\left(\frac{Q^{-1}(P_{fa}) - \gamma_{m,n}\cdot\sqrt{K/2}}{(1+\gamma_{m,n})}\right). \tag{12}$$

C. Cooperative Detection Model

Individual UAVs are limited in their sensing capabilities due to hardware constraints, restricting them to scanning only a narrow frequency range, defined as $(f_m^{\min}, f_m^{\max})$. If a target n transmits within this range, it is considered detectable. The target's transmission frequency is selected from a set f_n^t comprising multiple discrete channels $\{F'_n + j\Delta f_n\}$, where F'_n is the baseline frequency, Δf_n is the channel spacing, and $j \in \{1, \cdots, F_n\}$ indexes the channels, with F_n representing the total number of available channels. The detection probability of UAV m for target n at frequency f is given by:

$$P_{m,n}^f(\mathbf{p}_m, \eta_m) = \begin{cases} Q\left(\frac{Q^{-1}(P_{fa}) - \gamma_{m,n}\cdot\sqrt{K/2}}{(1+\gamma_{m,n})}\right), & f \in (f_m^{\min}, f_m^{\max}), \\ 0, & \textit{otherwise}. \end{cases} \tag{13}$$

To enhance detection, multiple UAVs cooperate by sharing local decisions χ_m (with $\chi_m = 1$ for detection and $\chi_m = 0$ for no detection) over synchronized communication links. These decisions are sent to a fusion center, where a logical OR rule is applied. The cooperative detection probability of M UAVs for target n at frequency f is given by:

$$P_n^f(\mathbf{p}, \eta) = 1 - \prod_{m=1}^{M}\left(1 - P_{m,n}^f(\mathbf{p}_m, \eta_m)\right). \tag{14}$$

D. Problem Formulation

To assess the overall sensing performance of the multi-UAV system, we define its sum detection probability as:

$$P_{\text{sum}}(\mathbf{P}, \boldsymbol{\eta}) = \sum_{n=0}^{N}\sum_{f=0}^{F_n} P_n^f(\mathbf{P}, \boldsymbol{\eta}). \tag{15}$$

A higher P_{sum} indicates better perception accuracy for the network. The objective is to maximize the sum detection probability by optimizing the UAVs' positions $\mathbf{P}$ and antenna orientations $\boldsymbol{\eta}$, formulated as:

$$\max_{\mathbf{P},\boldsymbol{\eta}} \quad P_{\text{sum}}(\mathbf{P}, \boldsymbol{\eta}) \tag{16}$$

s.t.

$$\mathbf{p}_m \in \mathcal{D}, \quad \forall m, \tag{16a}$$

$$\|\mathbf{p}_m - \mathbf{p'}_n\|_2 \geq S_{\min}, \quad \forall m, n, \tag{16b}$$

$$\|\mathbf{p}_m - \mathbf{p}_l\|_2 \geq R_{\min}, \quad \forall m \neq l, \tag{16c}$$

$$-\pi \leq \eta_m \leq \pi, \quad \forall m. \tag{16d}$$

In this formulation, (16a) specifies the deployable area for UAV m; (16b) ensures a minimum sensing distance between UAVs and targets; (16c) enforces a minimum separation between UAVs to avoid collisions; and (16d) limits the antenna orientation for each UAV.

III. Methodology

As per the expression of the formulated problem (16), it can be seen that the spatial constraints (16b) and (16c) are non-convex constraints set. Moreover, the objective function is inherently non-convex concerning interdependent variable $\mathbf{P}$ and $\boldsymbol{\eta}$ which makes it challenging for global optimization using the traditional gradient-based method. PSO is chosen for its ability to efficiently handle non-convex search spaces. Unlike gradient-based methods that may get trapped in local minima, PSO uses a swarm of particles that explore the space based on personal and global best values. This mechanism balances exploration and exploitation, preventing premature convergence. To address these complexities, we propose an iterative PSO-based algorithm that explores multiple solutions simultaneously, learning from collective experiences to effectively navigate the complex search space [16]. Additionally, a penalty-based fitness evaluation was adopted, further guiding particles toward feasible regions and managing non-convex constraints. By balancing exploration and exploitation, the algorithm efficiently identifies UAV configurations that maximize the sum detection probability while satisfying spatial and angular constraints.

A. PSO Representation and Initialization

In proposed PSO-based algorithm as shown in Fig. 1, each UAV initialize N_p particles in the search space, where each particle $\mathbf{s}_{i,m}^{(t)}$ for UAV m in iteration t includes its position and antenna orientation:

$$\mathbf{s}_{i,m}^{(t)} = \left[x_{i,m}^{(t)}, y_{i,m}^{(t)}, \eta_{i,m}^{(t)}\right], \tag{17}$$

with $\left(x_{i,m}^{(t)}, y_{i,m}^{(t)}\right)$ as UAV m's coordinates and $\eta_{i,m}^{(t)}$ its antenna orientation in iteration t. The swarm consists of N_p particles, where $i \in \{1, 2, \ldots, N_p\}$. Each particle $\mathbf{s}_{i,m}^{(t)}$ is initialized randomly within the deployable area $\mathcal{D}$, with $\eta_{i,m}^{(t)} \in [-\pi, \pi]$ for the antenna orientation. Initial velocities $\mathbf{v}_{i,m}^{(t)}$ are also randomly assigned to introduce variability, enhancing the search for optimal configurations. We model M UAVs, each with N_p particles, initialized randomly to explore and optimize detection probability.

B. Fitness Evaluation with Penalty Terms

In our proposed PSO-based algorithm, the fitness of each particle is evaluated based on the sum detection probability $P_{\text{sum}}(\mathbf{P}, \boldsymbol{\eta})$, with penalties applied for each constraint violations. The fitness function for particle i for m UAV in iteration t is given by:

$$\text{Fitness}_{i,m}^{(t)} = P_{\text{sum}}(\mathbf{P}_i, \boldsymbol{\eta}_i) - \lambda_{\text{penalty}} \sum_j \text{Constraint}_j, \tag{18}$$

where λ_{penalty} is a penalty coefficient, and Constraint_j represents the number of times the j-th constraint is violated, as per constraints (16a) to (16d). Each violation decreases fitness by λ_{penalty}, prompting the algorithm to increase fitness by reducing constraint violations. This penalty-based approach effectively guides the swarm of particles toward feasible solutions, ensuring all constraint are satisfied.

C. PSO-Based Optimization Algorithm

As outlined in Algorithm 1, the algorithm iteratively optimizes the position and orientation of each UAV, treated as an individual particle, by balancing both personal experience (personal best) and collective experience (global best). The inertia weight w is adjusted linearly from w_{max} to w_{min}, encouraging exploration in early stages and promoting convergence as the iterations reach T_{max}. The velocity and position updates are governed by (19) and (20) as follows:

$$\mathbf{v}_{i,m}^{(t+1)} = w \cdot \mathbf{v}_{i,m}^{(t)} + c_1 \cdot r_1 \cdot (\mathbf{p}_{i,m}^{\text{best}} - \mathbf{s}_{i,m}^{(t)}) + c_2 \cdot r_2 \cdot (\mathbf{g}^{\text{best}} - \mathbf{s}_{i,m}^{(t)}) \tag{19}$$

where w represents the inertia weight, c_1 and c_2 are acceleration coefficients, and r_1 and r_2 are random values from a uniform distribution $U(0, 1)$. The first term $w \cdot \mathbf{v}_{i,m}^{(t)}$ maintains the current direction, the second term drives the UAV toward its personal best, and the third term steers it toward the global best position of the entire swarm.

Algorithm 1 Iterative PSO-Based Optimization Algorithm for UAV Deployment

Input: w_{max}, w_{min}, c_1, c_2, N_p, T_{max}
Particle Initialization:
for each UAV $m = 1$ to M **do**
  for each particle $i = 1$ to N_p **do**
    Initialize $\mathbf{x}_{i,m}^{(0)}, \mathbf{y}_{i,m}^{(0)} \sim \mathcal{U}(\mathcal{D})$
    Initialize $\eta_{i,m}^{(0)} \sim \mathcal{U}(-\pi, \pi)$
    Set state $\mathbf{s}_{i,m}^{(0)} = [\mathbf{x}_{i,m}^{(0)}, \mathbf{y}_{i,m}^{(0)}, \eta_{i,m}^{(0)}]$
    Initialize $\mathbf{v}_{i,m}^{(0)} \sim \mathcal{U}(0, 1)$
    Compute $\text{Fitness}_{i,m}^{(0)}$ using (18)
    Set personal best $\mathbf{p}_{i,m}^{\text{best}} = \mathbf{s}_{i,m}^{(0)}$
  end for
end for
Optimization Process:
for each UAV $m = 1$ to M **do**
  for iteration $t = 1$ to T_{max} **do**
    Update inertia weight: $w^{(t)} = w_{\text{max}} - (\frac{w_{\text{max}} - w_{\text{min}}}{T_{\text{max}}}) \cdot t$
    for each particle $i = 1$ to N_p **do**
      Generate random numbers $r_1, r_2 \sim U(0, 1)$
      Update $\mathbf{v}_{i,m}^{(t+1)}$ using (19)
      Update $\mathbf{s}_{i,m}^{(t+1)}$ using (20)
      Clip $x_{i,m}^{(t+1)}$, $y_{i,m}^{(t+1)}$ within $\mathcal{D}$
      Clip $\eta_{i,m}^{(t+1)}$ within $[-\pi, \pi]$
      Compute updated $\text{Fitness}_{i,m}^{(t+1)}$ using (18)
      if $\text{Fitness}_{i,m}^{(t+1)} > \text{Fitness}_{i,m}^{\text{best}}$ **then**
        Update $\mathbf{p}_{i,m}^{\text{best}} = \mathbf{s}_{i,m}^{(t+1)}$
      end if
    end for
    Update $\mathbf{g}^{\text{best}}$ among all $\mathbf{p}_{i,m}^{\text{best}}$
  end for
  Set final position and orientation of UAV m to $\mathbf{g}^{\text{best}}$
end for
Output: Optimal UAV deployment positions and orientations, achieving the global best fitness from $\mathbf{g}^{\text{best}}$.

The updated position for each UAV m is then computed as,

$$\mathbf{s}_{i,m}^{(t+1)} = \mathbf{s}_{i,m}^{(t)} + \mathbf{v}_{i,m}^{(t+1)} \tag{20}$$

where each particle explores new regions by adjusting its position and orientation, updating $\mathbf{p}_{i,m}^{\text{best}}$ and $\mathbf{s}_{i,m}^{(t)}$ after each position update.

D. Parameter Selection and its Impact

The performance of the PSO algorithm depends on its parameters: inertia weight w balances exploration and convergence; cognitive (c_1) and social (c_2) coefficients regulate individual and global attraction, respectively. Random factors (r_1, r_2) enhance diversity, while particle count (N_p) and iterations (T_{max}) affect computational cost and solution quality. Fine-tuning these parameters and employing penalty-based fitness evaluation enables the algorithm to effectively solve the non-convex UAV deployment problem, optimizing detection probability under practical constraints.

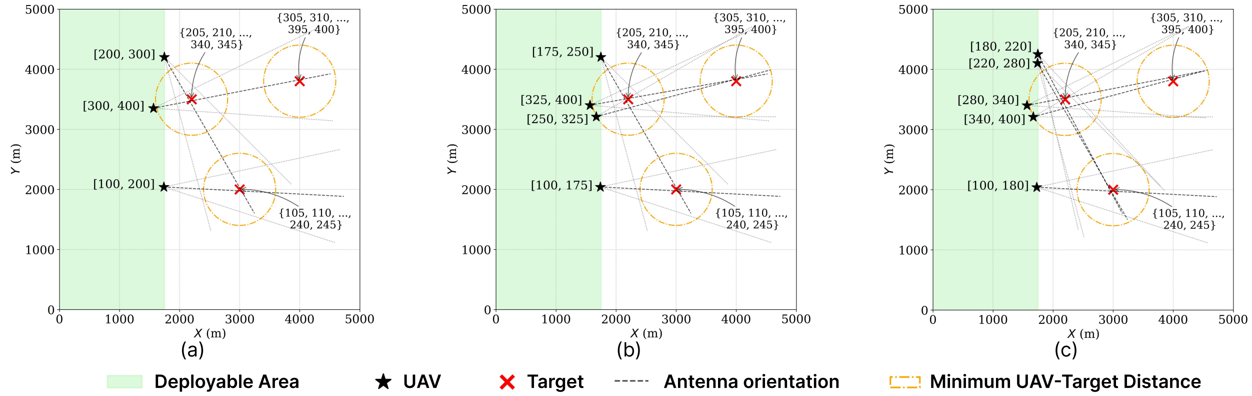

Fig. 2. Deployment results in multiple UAVs perceive multiple target scenarios: (a) $M = 3$, (b) $M = 4$, (c) $M = 5$

IV. Numerical Results

In this section, the numerical results of the proposed optimization method for a multi-UAV system are presented. We conducted simulations using Monte Carlo techniques to account for randomness in target positioning, measuring the dynamic deployment adaptation of multi-UAVs aimed to maximize detection probability in real-world perception scenarios. The simulation considers a network where multiple UAVs ascend to an altitude of 500 meters to minimize unnecessary energy consumption while cooperatively sensing three different targets. The coordinates of the targets are assumed to be $\mathbf{p}'_1 = (3000, 2500, 500)$ m, $\mathbf{p}'_2 = (2200, 3500, 500)$ m, $\mathbf{p}'_3 = (4000, 3800, 500)$ m, and the corresponding transmission frequency sets are $F_1 = \{105, 110, \ldots, 240, 245\}$ MHz, $F_2 = \{205, 210, \ldots, 340, 345\}$ MHz, and $F_3 = \{305, 310, \ldots, 390, 395\}$, MHz with each having the transmission power equal to 20 dBm. The UAVs are positioned in a 2D space of 1750 × 5000 square meters, while the observable space is 5000 × 5000 square meters. The parameter for proposed PSO are set by: $N_p = 50$, $w_{min} = 0.4$, $w_{max} = 0.7$, $c_2 = 1.5$, $c_2 = 2$, $\lambda_{penalty} = 10^6$ and $T_{max} = 200$, with additional simulation parameters detailed in Table I. To evaluate the proposed optimization approach, we examine two baseline methods:

- *ADPM-Based Scheme* [11]: This approach applies an Alternating Direction Penalty Method to optimize UAV positions and antenna orientations, enhancing convergence and detection probability in energy detection system model.
- *Non-Optimized Scheme*: In this scheme, UAVs are initially deployed randomly, assuming each UAV is assumed to sense all targets. Antenna orientations are then optimized using a Block Coordinated Descent algorithm.

Fig. 2 illustrates the optimized UAV deployment strategy using the proposed PSO-based algorithm across different UAV counts. For UAVs assigned to single-target sensing, deployment is optimized at minimal allowable distances from their targets to enhance SINR and detection probability; for instance, in Fig. 2a, the UAV with the sensing band [100, 200] MHz is positioned close to target 1 along the deployable region's edge.

TABLE I: Simulation Parameters

Parameters	**Value**
Flight altitude H	500 m
Minimum UAV-target distance $S_{\min}$	500 m
Collision avoidance distance $R_{\min}$	200 m
Number of sampling points K	1000
Specified false alarm probability P_{fa}	0.001
Directional antenna's beamwidth θ	20°
Number of isotropic antenna elements N_t	7
Channel power gain β_0	-20 dB
Power of AWGN σ_n^2	-80 dBm

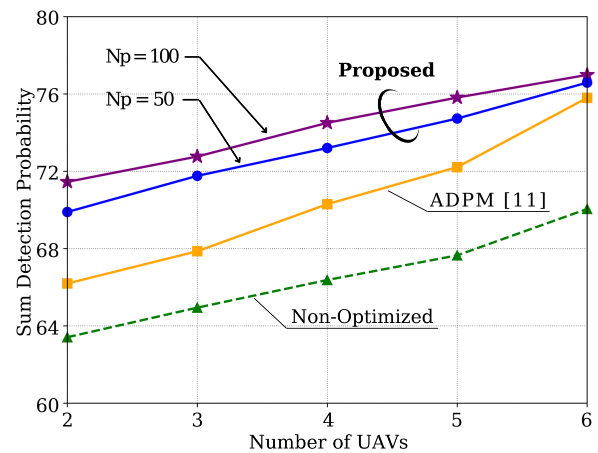

Fig. 3. Comparison of sum detection probabilities with varying numbers of UAVs across different schemes.

In contrast Fig. 2c, UAVs tasked with multi-target sensing, such as one operating in the [180, 220] MHz band for targets 1 and 2, are strategically positioned to balance proximity and orientation. This placement enables effective multi-target detection by aligning antenna orientations to maintain optimal detection across multiple targets.

To ensure statistical reliability, each experiment was repeated over 100 Monte Carlo runs, and 95% confidence intervals were calculated for all detection probability metrics. As shown in Figures 2 and 3, the confidence intervals for UAV counts from 2 to 6 are as follows: for 2 UAVs ±0.6820, for 3 UAVs ±0.3591, for 4 UAVs ±0.3202, for 5 UAVs ±0.2883, and for 6 UAVs ±0.1288. This indicates reduced performance variability and

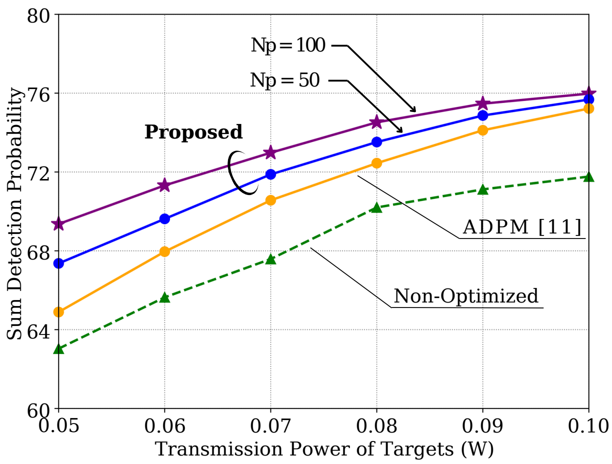

Fig. 4. Comparison of sum detection probabilities with varying target transmission power across different schemes.

improved system reliability as the number of UAVs increases. However, when the confidence interval stops significantly decreasing with an increase in UAV count, it suggests an optimal number of UAVs, beyond which additional UAVs provide diminishing returns. To compare the detection performance of the proposed PSO with ADPM [11] and Non-Optimized schemes, we randomly positioned the targets and used each algorithm to optimize UAV deployment and antenna orientation for maximum detection probability. The results, shown in Fig. 3, indicate that the proposed PSO scheme outperforms the others, particularly with fewer UAVs. Specifically, it provides a 7.94% improvement with 2 UAVs and a 7.21% improvement with 3 UAVs over the ADPM-based scheme due to effective SINR optimization. This improvement is attributed to the PSO scheme's ability to balance exploration and exploitation in navigating non-convex spaces.

Fig. 4 illustrates the effectiveness of the proposed EBD approach aided by proposed PSO optimization, which achieves higher detection probabilities, particularly at lower transmission power levels. This advantage is due to the adopted method does not require prior noise information, making it reliable in dynamic environments. The results confirm that the eigenvalue-based approach, combined with optimal deployment and antenna orientation from the proposed PSO algorithm, maintains high detection probabilities under diverse conditions. Increasing the particle count N_p further enhances detection performance and algorithm robustness in multi-UAV sensing; however, it raises computational costs, necessitating a balance between performance and resource efficiency.

V. Conclusion and Future Work

In this paper, we enhanced multi-UAV cooperative sensing by integrating EBD with a PSO-based optimization algorithm to effectively navigate non-convex search spaces and jointly optimize UAV deployment and antenna orientation. By incorporating a penalty-based approach within PSO, we guided solutions toward feasible regions despite complex spatial constraints. Monte Carlo simulations demonstrated that our proposed method outperforms the ADPM-based scheme, achieving superior detection performance without the need for prior noise knowledge, making it ideal for dynamic environments. This work provides valuable insights for designing robust multi-UAV systems, with applications in adaptive target tracking, distributed recognition, and dynamic monitoring. Future work will investigate sensor fusion techniques to address inefficiencies in UAVs detecting the same transmission.

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