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ARTICLE

Decentralized underwater AUV search and self-allocation for multiple targets using ad hoc networking-aided firefly scheme

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Underwater AUV swarms can explore large regions and search for multiple targets in parallel but the limited range of acoustic links and the absence of infrastructure make decentralized self-allocation challenging. This paper presents the Ad hoc network Assisted Firefly system (AA-FY), a firefly-inspired method integrating sensing, multi hop underwater ad hoc communication, and movement. It bridges Multi-Robot Task Allocation (MRTA) and Multimodel Optimization (MMO) for a robotic search system, where MMO is a theoretical guide solving an MRTA problem. System-wise, AA-FY applies a bio-inspired movement strategy to accomplish the search and self-allocation for aggregations at multiple targets. The ad hoc strategy allows information to be aggregated and disseminated only when superior information arrives. It also guides the movement using an attenuation clue based on hop counts. Such strategies encourage localized convergence and stable niches around multiple targets. Further, AA-FY uses a greedy selection strategy to drive each AUV toward the most influential attenuated candidate without a central controller or global map. The evaluations show that AA-FY reliably allocates clusters of AUVs around all targets. It even succeeds when targets are far apart or spatially biased. AA-FY also achieves proportional allocation according to target signal strength.

Keywords: AUVs, firefly algorithm, swarm search, underwater ad hoc network

1. INTRODUCTION

The deep sea remains one of the Earth's great frontiers, holding vast potential for scientific discovery, resource management, and strategic operations. Ongoing expeditions consistently prove this by revealing startling new species and geological features. For example, recent 2024 explorations of the Nazca and Salas y Gomez underwater mountain ridges off the coast of Chile, led by the Schmidt Ocean Institute, resulted in the potential discovery of over 150 new species, including deep sea corals, glass sponges, and squat lobsters [1]. These expeditions also mapped 52 777 square kilometers of the seafloor, discovering four previously unknown seamounts in the process. Underwater vehicles are critical in scanning immense, difficult to reach areas of the seabed. In the mission of "In Search of Hydrothermal Lost Cities", both Remotely Operated Vehicles (ROVs) and autonomous underwater vehicles (AUVs) were launched from Research Vessel Falkor, along with other sampling instruments like sonar, CTD sampling [2].

The vast ocean areas and the immense costs and time associated with the explorations, or similar, have accelerated the focus on robotic systems, particularly Autonomous Underwater Vehicles (AUVs), as reported in [3], "swarms of underwater drones are helping researchers learn more about our most important, and least understood, natural resource."

In this article, we envision a scenario in which a swarm of AUVs cooperates via an underwater ad hoc network to search for multiple underwater targets at the same time. Exploring complex deep sea ecosystems can benefit greatly when the exploration is not for a single target but a vast region with multiple features of varying scientific values, e.g., locating specific high priority targets like active hydrothermal vents has the highest priority, while mapping broader geological structures is also crucial but of secondary importance. As such, the cooperative potential is critical in reducing the time and the cost in surveying these expansive and dynamic underwater frontiers.

Although significant technical progress has been made in autonomous underwater vehicles and underwater acoustic communications and networking, how communications can truly help swarm autonomy and scalability remains a challenge. Related work in underwater ad hoc networking for AUV swarms focus on maintaining connectivity, improving packet delivery, or enhancing localization accuracy [4, 5]. Only a few recent studies start to couple network design with higher-level swarm objectives such as task allocation, cooperative mapping, or adaptive formation control [6, 7]. In these areas of work, the swarm behavior, the behavior of search and self-allocation is not the focus. Thus, there is still a gap between the communication-centric design found in the related work and a holistic design not only on networking but also with a focus on assisting swarm-level decision making. In this paper, we address this gap by explicitly incorporating underwater networking constraints into the design of the AUV swarm search and allocation strategy.

To assist swarm–level decision-making for searching multiple targets and aggregating them, a key challenge is deciding how to find the target and also split up to handle multiple tasks or targets. This problem is known as Multi-Robot Task Allocation (MRTA) [8]. This paper addresses the MRTA problem in the specific scenario where there are an unknown number of targets located at unknown places within the search area with various significant values. The job for the AUV swarm is to find all targets and allocate themselves to these targets in a purely self-organized manner. In the optimization research field, this scenario maps directly to the Multimodal Optimization (MMO) problem [9]. We interpret MMO in the context of robotic search by treating the physical underwater environment as a complex, unknown objective function, where the signal emissions of distinct targets represent multiple local or global optima. Unlike traditional optimization that seeks a single best solution, MMO aims to locate and maintain solutions at multiple peaks. By bridging MRTA and MMO, our system uses the theoretical principles of MMO niching, where agents form stable sub-populations at each optima, to achieve the physical task allocation of distributing AUVs among multiple discovered targets.

In this paper, we propose a robotic search system that solves the MRTA problem using MMO as a theoretical guide and applying a bio-inspired movement strategy for accomplishing search and self-allocation to aggregate multiple targets. For the latter, a well-known example of the firefly algorithm [10] is used. The firefly algorithm mimics how fireflies find each other using flashing lights [10]. The algorithm is designed to find the single best solution while ignoring other local optima. The proposed work applies the MMO principle to the firefly algorithm for searching multiple optima. To better understand how the firefly algorithm applies to AUVs, it is helpful to establish a direct analogy. In our system, each "firefly" is an Autonomous Underwater Vehicle (AUV). The "flashing lights" or "brightness" of a firefly represents the strength of a localized environmental signal sensed by the AUV, such as the concentration of dissolved methane from a hydrothermal vent or the acoustic signature of a lost artifact. A "local optimum" in the mathematical landscape corresponds to the physical location of one of these distinct targets. Therefore, when a less bright firefly moves toward a brighter one, it physically represents an AUV moving up a chemical or acoustic gradient by following the lead of a teammate that has detected a stronger signal.

Our initial proof-of-concept test shows that when the individual search agent's communication range is constrained, the firefly algorithm can achieve an MMO search. However, the constrained communication range also creates another problem. Due to the vast space of the search area, only a limited number of agents can eventually reach the optima. Such a test led to the design of an ad hoc communication-assisted firefly (AA-FY) search scheme. This new method allows the AUV swarm to find multiple targets and form stable groups around them. The algorithm works in a decentralized way, meaning each AUV makes its own decisions based only on what it can sense and the information it gets from nearby teammates. Our approach ensures that the number of AUVs that gather at each target is proportional to the target's signal strength or importance.

The ad hoc communication strategy in AA-FY not only processes information leading to a target, but also propagates it through the whole swarm. The ad hoc communication allows the AUVs to form a multihopped wireless network. Through this ad hoc network, one AUV can share its finding with the AUVs located beyond the communication range. The outcomes of the evaluation show that with the help of the ad hoc network, all the AUVs in the swarm will be allocated to the targets once they are found as long as the network is connected.

The proposed AA-FY swarming system consists of three modules, which are the sensing module, the communication module, and the movement module. These three modules define the three essential behaviors that each AUV needs to perform when conducting the target search and self-allocating operation. All three modules are operated upon the one essential data structure, the brightness table. This table records the locations of the best historical clues leading to a search target that is found by each AUV. To achieve self-allocation to multiple search targets, a hop-count-based brightness adjustment scheme is developed in the design of the communication and movement modules. The basic idea is that the more hops a clue message needs to travel from sender AUV to the receiver AUV, the less impact this clue will have on the receiver AUV's next movement decision. With the help of this hop-count-based brightness adjustment scheme, AA-FY ensures that the number of AUVs gathering at each target is proportional to the target's signal strength.

The rest of this paper is organized as follows. Section 2 briefly summarizes related work in task allocation and underwater ad hoc networking. It also includes a brief introduction of the firefly algorithm. Section 3 introduces the preliminary work of the revised MMO algorithm and preliminary evaluation. Section 4 defines the search and self-allocating problem and addresses several assumptions for the AA-FY system. Section 5 describes multiple components of the proposed AA-FY system. Section 6 presents the experimental setup, followed by the results and discussions. Finally, Section 7 concludes the work with suggestions for future work.

2. RELATED WORK AND BACKGROUND

The underwater robotic operation discussed in this work is to let a group of AUVs search and be allocated to multiple search targets. Meanwhile, such collective and cooperative operations are based on underwater ad hoc networking. Naturally, the proposed AA-FY system relates to two research areas. One is the robotic search and allocation missions, and the other is ad hoc communication technologies for underwater mobile devices including AUVs. Existing work related to these two research areas is briefly discussed in this section. In addition, since the proposed system builds upon the firefly algorithm, a short overview of the algorithm is introduced later in this section.

2.1 Multi-Robot search and allocation

Multi-agent coverage control provides an important foundation for our problem of allocating multiple UAVs to spatially distributed Areas of Interests (AoIs). Song et al. [11] recently proposed a coverage algorithm for multi-agent systems that can autonomously detect and cover *unknown* target areas. Their method combines a dynamically constructed density function with Centroidal Voronoi Tessellation (CVT) and control barrier functions to safely guide agents toward multiple disjoint regions without prior knowledge of their locations. For aerial platforms, Feng and Katupitiya [12] studied UAV-based persistent full area coverage with dynamic priorities, modeling the environment as a grid whose cells receive time-varying importance weights. Zhang et al. [13] addressed multi-UAV persistent monitoring of dynamic Points of Interest (POIs) and introduced a distributed task-allocation framework (IRADA) that integrates information gain, energy constraints, and communication into a single reward landscape. However, these areas of work generally assume that the underlying region or POI set is known and focus more on how to revisit or rebalance known tasks rather than on discovering previously unknown AoIs.

A second line of work focuses on multi-UAV searches, connectivity maintenance, and surveillance. Yanmaz et al. [14] formulated dynamic path planning for multiple UAVs performing multi-target searches while preserving network connectivity, explicitly considering that target locations are initially unknown and must be revealed through sensing. Patrinopoulou et al. [15] developed a decentralized multi-agent system for area surveillance and intruder monitoring, where agents use local decision-making rules to patrol and react to detected intruders. On a smaller scale, Sung et al. [16] studied environmental hotspot identification with a single UAV under tight time constraints, using an informative path planning strategy that trades off exploration and exploitation of high-value regions. Together, these areas of work demonstrate how distributed policies can support search and surveillance in large environments, but they typically do not couple the discovery of new AoIs with a formal, multi-UAV allocation mechanism that balances load across many emerging regions.

More recently, Deep Reinforcement Learning (DRL) has been used to tightly couple task assignment and motion planning. Kong et al. [17] formulate simultaneous target assignment and path planning as a Partially Observable Markov Decision Process (POMDP) in 3D cluttered environments, and train a TD3-based policy that jointly decides which target each UAV should pursue and which collision-free trajectory it should follow. From a broader perspective, Ghauri et al. [18] survey multi-UAV task-allocation algorithms for search-and-rescue scenarios, highlighting trends from centralized, static formulations toward dynamic, distributed schemes that better reflect realistic communication and energy constraints. The literature thus splits between methods that excel at discovering unknown regions but rely on relatively simple coordination rules [11, 16] and methods that optimize allocation for a predefined task set [19, 20, 17]. The problem addressed in this paper sits at their intersection: enabling a swarm of UAVs to autonomously discover multiple previously unknown AoIs and self-allocate across them in a balanced, resource-aware, and communication-constrained manner.

Task allocation for multi-UAV systems has often been treated as a separate combinatorial optimization problem and solved by swarm algorithms. Early work by Sujit et al. [19] used Particle Swarm Optimization (PSO) to allocate a set of known tasks to multiple UAVs, minimizing overall mission cost while handling constraints such as limited endurance. Building on this direction, Li et al. [20] proposed a multi-mechanism swarm optimization algorithm that simultaneously assigns inspection segments and plans collision-free paths for multi-UAV transmission-line inspection under complex wind fields, while Yao et al. [21] designed a hybrid ant colony-based strategy for extensive search by a UAV swarm in unpredictable environments, explicitly accounting for energy, formation, and safety constraints. These metaheuristic approaches are well suited to high-dimensional, constraint-rich formulations but typically assume that the set of tasks or regions of interest is known beforehand and encoded into the optimization problem.

Recent advances in swarm intelligence-based MRTA have increasingly emphasized multimodal optimization to address the inherent degeneracy and structural redundancy of allocation spaces. The work entitled "A Novel Multimodal Multi-Objective Optimization Algorithm for Multi-Robot Task Allocation" [22] recognizes MRTA as a multi-objective optimization problem, but also a multimodal optimization problem when considering real deployment environments or the preferences of the tasks. The work describes an improved multimodal multi-objective differential evolution algorithm hybrid with a simulated annealing algorithm, such that enough solutions/schemes can be provided to improve the stability and flexibility of the multi-robot system. Typically, a population initialization method and a redundant solution detection technique are proposed to improve population diversity and save computational resources. The simulated annealing algorithm is used to improve the search capability for finding promising solutions. In another work, namely, "Strengthening Evolution-Based Differential Evolution with Prediction Strategy for Multimodal Optimization and Its Application in Multi-Robot Task Allocation" [23], the evolution process is accelerated by using predictive mechanisms that estimate promising search regions. It also uses strategy to help inferior individuals to jump out of local optima and converge faster. When applied to MRTA, such prediction-guided evolution can improve computational efficiency and scalability, especially in large-scale allocation problems. It is interesting to note that these two papers show two complementary approaches for swarm-based MRTA. Specifically, the former prioritizes structural diversity in algorithms, whereas the latter emphasizes evolutionary acceleration and predictive search efficiency. They suggest that effective MRTA algorithms should both discover multiple equivalent allocations and improve evolutionary search efficiency for robust multi-robot decision-making in complex environments.

In summary, the proposed AA-FY distinctly departs from existing MRTA and swarm search methods in three key ways: First, while traditional MRTA often treats task allocation as a separate computational step performed on known tasks, AA-FY tightly couples the physical search and the allocation process. In AA-FY, discovery and assignment occur simultaneously. Second, unlike methods that rely on a priori knowledge of target locations or a centralized coordinator, AA-FY operates in a completely unknown environment relying strictly on localized, decentralized decision-making. Finally, rather than using an optimization algorithm merely as an abstract solver for a discrete assignment problem, AA-FY embeds the continuous optimization process of MMO directly into the physical movement and ad hoc communication rules of the AUVs, making the swarm's physical distribution the solution itself.

2.2 Underwater ad-hoc networking

Cooperative Autonomous Underwater Vehicles (AUVs) rely on Underwater Ad Hoc Networking (UANET) for exchanging messages, such as sensed data, navigation information, task status, and command-control. Over the decades, researches have addressed severe physical limitations of underwater acoustic communications including limited bandwidth, high and variable propagation delays, Doppler effects, intermittent connectivity, etc. While the constraints on the design of multi–AUV swarm, or multi–robot cooperation remain the same, recent trends call for the co–design of communication, localization, and control [24, 25].

Extensive research on UANET has focused on routing protocols, with or without the assistance of location information. For example, localization–based and localization–free schemes, depth–based routing, and delay/disruption–tolerant approaches [24, 26, 27, 28]. However, most of these protocols were originally designed for static or sparsely mobile sensor deployments, rather than tightly coupled AUV swarms.

Several area of work have focused specifically on communication for AUV swarms. Gussen et al. optimize acoustic communication links and network topology to improve localization accuracy and information-sharing to help AUV formations [5]. Hoeher et al. present a tutorial on underwater optical wireless communications in swarm robotics, viewing a swarm of AUVs as a vehicular ad hoc network with highly dynamic topology [4]. More recently, Huo et al. and Wang et al. propose unified systems for communication, positioning and navigation in AUV swarms, including asynchronous multi–cluster network architectures and hybrid MAC protocols tailored to clustered swarm operation [6, 7]. In parallel, localization techniques based on underwater acoustic networks have been studied. Some work is developed explicitly for low–cost swarm deployments, with focuses on how network geometry would affect collective pose estimation [29, 30].

While the above-mentioned work relates to the proposed AA-FY, significant differences exist. Most underwater ad hoc networking research for AUV swarms treats the swarm behavior as given and concentrates on maintaining connectivity, improving packet delivery, or enhancing localization accuracy. Only a few recent studies start to couple network design with higher–level swarm objectives such as task allocation, cooperative mapping, or adaptive formation control. Consequently, there is still a gap between the communication–centric design and swarm–level decision making. In AA-FY, we address this gap by explicitly incorporating underwater networking constraints into the design of the AUV swarm search and allocation strategy.

Several existing studies have integrated ad hoc networking into the design of robotic swarm search schemes, where agents organically maintain a network to facilitate cooperative operations. For land-based multi-robot systems, Couceiro et al. [31] extended Particle Swarm Optimization (PSO) and Darwinian PSO (DPSO) into Robotic PSO (RPSO) and Robotic DPSO (RDPSO), respectively. These algorithms leverage a Mobile Ad hoc Network (MANET) and incorporate mechanisms such as social exclusion and inclusion to enhance optimization performance and mitigate the risk of local optima while addressing physical constraints like obstacle avoidance. Similarly, the Ad hoc Communication Assisting Distributed Particle Swarm Optimization (AA-DPSO) scheme introduced in [32] aims to improve cooperative underwater search operations for AUV swarms. This approach utilizes multihop acoustic communication to disseminate high quality search data across the swarm, effectively overcoming the severe range and reliability constraints inherent in underwater environments. Notably, the AA-DPSO framework employs a communication strategy identical to the ad hoc mechanism utilized in the proposed AA-DGSO scheme for facilitating search operations.

The aforementioned studies primarily address the problem of localizing a single, definitive target amidst multiple false targets, which serve as environmental distractions (i.e., local optima). In these frameworks, a successful search operation culminates in the entire robotic swarm aggregating exclusively at the true target's location. In contrast, the proposed AA-FY scheme is designed for a fundamentally different operational context wherein all identified targets within the search space are considered legitimate and require concurrent attention. This scenario is more like a typical MMO optimization objective process. Consequently, the objective of the AA-FY scheme is not singular convergence but rather the proportional distribution and allocation of the AUV swarm across multiple valid targets.

2.3 Firefly algorithm

The firefly algorithm, introduced by Xin-She Yang in 2008 [10], is a nature-inspired metaheuristic optimization algorithm based on the flashing behavior of fireflies. In the algorithm, each firefly represents a candidate solution in the search space, and its brightness is determined by the objective function.

The algorithm assumes the following three rules:

1. All fireflies can be attracted to each other.
2. Attractiveness is proportional to brightness and decreases with distance.
3. A less bright firefly moves toward a brighter one. If no brighter firefly is found, it moves randomly.

The attractiveness β between two fireflies is defined as:

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{1}$$

where β_0 is the attractiveness at $r = 0$, γ is the light absorption coefficient, and r is the distance between two fireflies.

The movement of a firefly i toward a brighter firefly j is given by:

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2}(x_j - x_i) + \alpha\,\epsilon \tag{2}$$

where α is a randomization parameter and ϵ is a random vector drawn from a uniform or Gaussian distribution.

The standard firefly algorithm is fundamentally designed for unimodal or global optimization. The firefly algorithm's global attraction mechanisms inevitably cause the entire swarm to converge on a single, brightest target, discarding other valuable local optima. However, the problem described in this paper is to distribute AUVs to multiple search targets. To achieve this, our proposed approach deliberately modifies the standard behavior. By incorporating an unavoidable communication range constraint created by the underwater environment and a novel hop-count-based brightness attenuation, AA-FY disrupts global convergence, intentionally fostering "niching" behavior that allows distinct sub-swarms to form and stabilize around multiple search targets (local optima in the optimization sense) simultaneously.

Algorithm 1 Multi-targeted firefly algorithm (MFA)

1: **Initialize Algorithm Parameters:**
2: $n \leftarrow$ Population size (number of AUVs)
3: MaxGeneration $\leftarrow$ Maximum search steps
4: $\alpha \leftarrow$ Randomization parameter (exploration noise)
5: $R_{comm} \leftarrow$ Acoustic communication range
6: $f(\mathbf{x}) \leftarrow$ Environmental signal strength at location $\mathbf{x}$
7: $\mathbf{x} \leftarrow$ Initial deployed positions of all AUVs
8: $\mathbf{I} \leftarrow f(\mathbf{x})$ ▹ Initial sensed signal strengths
9: **Main Loop:**
10: $t \leftarrow 0$
11: **while** $t <$ MaxGeneration **do**
12:     **for** $i = 1$ **to** n **do** ▹ For every AUV...
13:         **for** $j = 1$ **to** n **do** ▹ ...evaluate every other AUV
14:             $r_{ij} \leftarrow \|\mathbf{x}_i - \mathbf{x}_j\|$ ▹ Calculate physical distance
15:             **if** $I_j > I_i$ **and** $r_{ij} < R_{comm}$ **then** ▹ If neighbor j senses a stronger signal AND is within acoustic range
16:                 $\mathbf{x}_i \leftarrow \mathbf{x}_j + \alpha(\text{rand} - 0.5)$ ▹ Move AUV i toward AUV j, add slight random exploration
17:                 $I_i \leftarrow f(\mathbf{x}_i)$ ▹ Update sensed signal strength at new location
18:             **end if**
19:         **end for**
20:     **end for**
21:     $t \leftarrow t + 1$
22: **end while**

3. MULTI-TARGETED FIREFLY ALGORITHM

The firefly algorithm was originally proposed as a swarm optimization algorithm for a single optimal. Agents being attracted by local optima is undesirable and should be avoided in the optimization process. However, in AA-FY, such attractions are considered helpful in solving the multi-target problem. For the latter, each local optimum is considered as a target or an AoA that needs to be taken care of by AUVs. For example, there could be multiple oil spill sources that need to be contained by AUVs. In this section, both the new algorithm Multi-targeted firefly algorithm (MFA) and related evaluations are introduced in detail.

3.1 The multi-targeted firefly algorithm

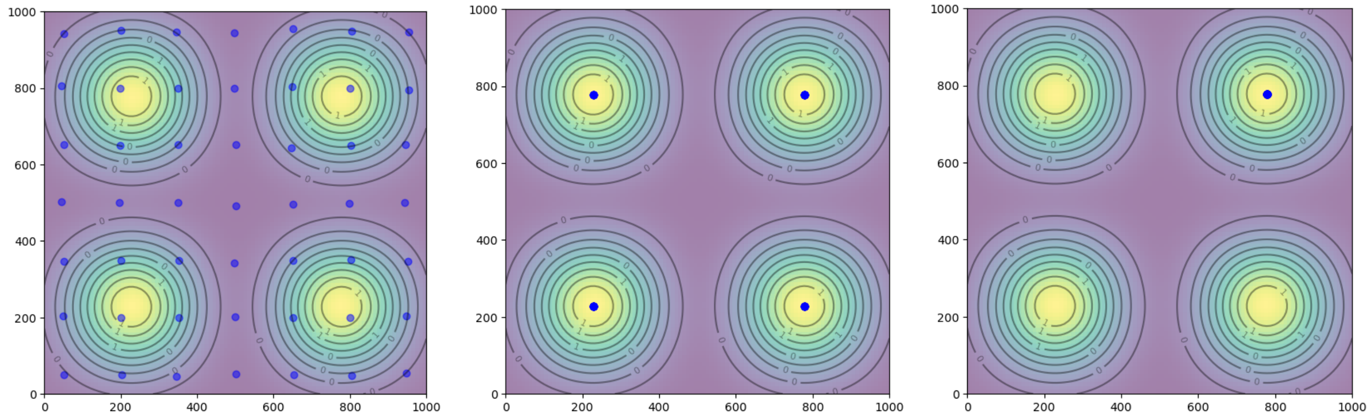
The very parameter that controls whether the fireflies converge at the global optimum or are attracted by multiple local optima is the light absorption coefficient γ in equation *(2)*. This light absorption coefficient mimics the fact that the brightness of the light will be dimmer when distance increases. Thus, a suitable γ will let the firefly algorithm encourage local optima to attract the surrounding fireflies.

In a real-world environment, the light emitted by the fireflies can only travel a limited distance. In real applications, the light could be the chemical strength from an emitting source. We model this physical constraint by introducing a communication range limit R_{comm} into the firefly algorithm. The modified algorithm is shown in Algorithm 1.

Here, R_{comm} at line 17 is the communication range limit. A firefly i will only be attracted to a brighter AUV j if the distance between them, r_{ij}, is less than R_{comm}. This simple rule prevents AUVs from being drawn to a very distant, strong target. Instead, they only respond to the brightest AUV within their local neighborhood, which naturally encourages the formation of multiple, separate clusters.

3.2 Evaluating MFA

Evaluations are performed to validate whether MFA truly allows agents to find and converge on multiple search targets under multiple communication ranges. The evaluation has 49 fireflies deployed at the grid points in a square-shaped grid (Fig.1a and Fig.2a). Each of these fireflies is represented by a blue dot. The environment contains four discrete targets, which are represented by a composite fitness contour landscape. To simulate an environment featuring multiple distinct targets, the underlying fitness function is constructed by combining four inverted Easom functions. In the resulting contour map, each target is characterized by its own sphere of influence, visualized as multiple layers of concentric circles. The bright yellow color denotes the center of the search target (i.e., the location of maximum fitness), while the purple color indicates areas where no significant target signal is detectable.

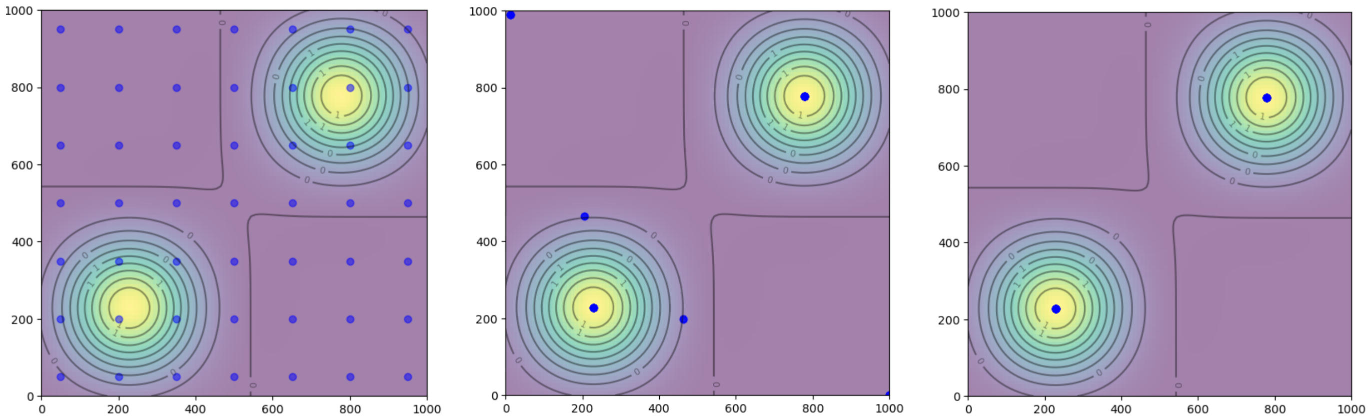


(a) Initial Deployment

(b) R_{comm}: 200 - 500

(c) R_{comm}: 600 - 1000

Figure 1 – Effect of communication range (R_{comm}) on AUV swarm distribution over four targets



(a) Initial Deployment

(b) R_{comm}: 200

(c) R_{comm}: 500

Figure 2 – Effect of communication range (R_{comm}) on AUV swarm distribution over two targets

The parameter R_{comm} dictates how far an AUV's "brightness" information can travel. When R_{comm} is 100m, it is shorter than the initial 150m spacing between AUVs. Consequently, no AUV receives information from its peers, and the swarm remains completely static, matching the initial state in Fig. 1a. However, when R_{comm} is set between 200m and 500m, an ideal "niching" behavior emerges. As seen in Fig. 1b, AUVs only interact with local neighbors, allowing the swarm to naturally break into four distinct groups, each discovering and converging on a different local target. Conversely, if R_{comm} is too large (greater than 600m), the algorithm reverts to standard global optimization behavior. As shown in Fig. 1c, a single AUV finding a strong signal broadcasts it to nearly the entire swarm, causing all AUVs to converge on a single location and abandon the other valuable targets.

The second evaluation places fewer search targets in the search area. Fig. 2 shows that a 200m communication range is not sufficient when only two targets exist, while a 200 communication range works in the earlier four-target setting. Due to the lack of gradients information in the upper left and lower right sections of the search space, fireflies in these areas cannot properly find a lead to a target. Neither can they receive from others easily, leading to wandering around randomly, or stuck at a corner or boundary. In the end, only 31 out of 49 fireflies reach either of the two targets. Increasing the communication range to 500m can solve this problem as shown in Fig. 2c. However, in real-world underwater scenarios, increasing an AUVs' transmission range is not always an option. Increasing the communication range usually means increasing transmission power, which will put a lot of energy burden on the limited battery capacity. Thus, using an ad hoc communication scheme is necessary here since it is the equivalent of increasing transmission range without really increasing transmission power.

4. PROBLEM STATEMENT AND ASSUMPTIONS

4.1 Problem statement

The evaluation of the MFA shows that the MFA can successfully help distribute AUVs to different underwater targets. But challenges also exist for it to serve as an

AUV controlling scheme when facing dynamic resources and mission environments. Firstly, MFA only works in a macro sense with global knowledge. All fireflies' positions are adjusted by the algorithm at the same time. In real application, when AUVs are deployed underwater, one cannot expect a centralized controlling unit to collect brightness info from AUVs nor give commands to each AUV for their next movement. A distributed controlling scheme that can work on the individual AUV is needed in this scenario. Secondly, the results indicate that a carefully selected firefly R_{comm} is very important for properly distributing the fireflies to each target. If too small, not all AUVs are able to converge to a target properly. If too large, all AUVs may be attracted to a single point. Dynamically adjusting R_{comm} during the search process would be a desirable method to avoid the dilemma. However, changing communication range is not easy when AUVs are deployed in the sea. Communication range also depends on the transmission power of the signal emitter. But an AUV only has a very limited selection of the transmission power they can choose. The third problem is that increasing transmission power will also increase the power consumption of AUVs, which may lead to early battery depletion. As a consequence, the inflexible choice of communication range is another major hurdle to applying MFA to the AUV swarm.

These problems call for a distributed coordination and control scheme and help from ad hoc communication to handle diverse application requirements from varying numbers of AUVS, targets, insufficient information, and a lack of global coordination.

4.2 AA-FY system assumptions

The AA-FY system is built with several necessary assumptions for the applicability of its targeted goals. They are described below.

- The search environment is a 2D rectangular area with no obstacles. This is a common setup for underwater searches where the horizontal area is much larger than the depth. Within this area, there are multiple targets waiting to be found. All targets emit signals that the AUVs can sense.
- All the signals emitted by the target may have different strengths.
- When the mission starts, all AUVs are already deployed on the seafloor on a square grid. They begin to sense, move, and communicate right away. As a group, they will gradually form a rough idea of where the real target might be.
- The AUVs' movement is simplified to a 2D plane to reduce the computing power needed for simulations. This simplification is consistent with methods used in previous studies (e.g., [33, 34, 35, 36]).

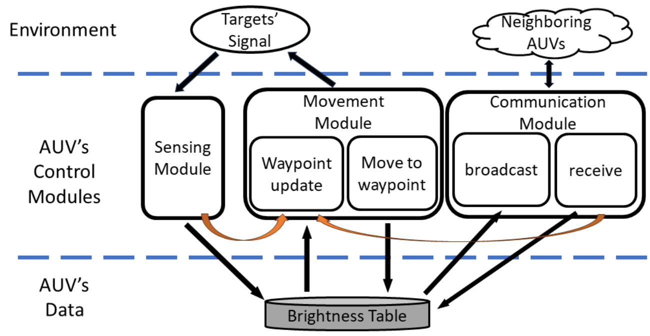
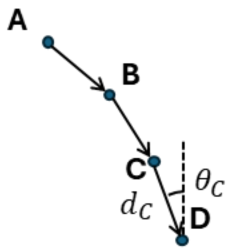


Figure 3 – AA-FY system overview

- All AUVs travel at a fixed speed of 3 knots (or 1.54 m/s).
- The only prior knowledge the AUV swarm has about the search area is the search area's size and boundaries. The AUVs' swarm has no knowledge about the exact location of the search target initially. They also know the total number of AUVs in the swarm and their own individual ID. But the locations of other AUVs are unknown.
- The AUVs use underwater acoustic communication to talk to each other. However, this communication has a limited range; AUVs must be within a certain distance to communicate.
- AUVs do not have access to a global underwater positioning system. However, each AUV is equipped with a compass to help it navigate through the water.
- The acoustic signal transmission power is fixed and known to all AUVs. This allows an AUV to use the Received Signal Strength Indicator (RSSI) to measure the distance to the source. Additionally, AUVs can detect the Angle of Arrival (AoA) of a received signal. By using both the RSSI and AoA, an AUV can figure out the location of another AUV when it receives a message from it.
- The Media Access Control (MAC) protocols (like CSMA/CA and TDMA) are assumed to be installed on all AUVs to handle issues like packet collisions. The communication strategy proposed in this work operates at the network layer, building on top of the MAC layer.

5. AA-FY SYSTEM DESIGN

The AA-FY system regards individual AUVs as fireflies in facilitating autonomous navigation within a defined search space, relying solely on local communication. The proposed AA-FY system has three core modules: sensing, communication, and movement. Central to the system's operation is a crucial internal data structure, the brightness table, maintained at each AUV. The three core modules, as well as their interaction with the brightness table, are shown in Fig. 3. The subsequent subsections introduce the detailed design of the brightness table and the functionalities of each module.



ID	Distance	Angle	Brightness	Hop
A	d_A	θ_A	b_A	3
B	d_B	θ_B	b_B	2
C	d_c	θ_C	b_C	1
D	0	0	b_D	0

Figure 4 – Brightness table example

5.1 Brightness table

The decision-making process within the AA-FY scheme relies critically on the brightness table, a dynamic data structure maintained individually by each AUV. This table functions as a localized knowledge repository, storing vital information about all known neighboring AUVs. Specifically, for each entry, the table captures the following details:

- **ID:** Unique integer identifying the AUV.
- **Distance:** Euclidean distance between the current AUV and the best position found by the other AUV.
- **Angle:** Relative angle to the best location found by the other AUV, expressed with distance in polar coordinates.
- **Brightness value:** The fitness value (brightness level) of that AUV's best recorded position.
- **Hop:** The number of hops for another AUV's message to reach the current AUV through the multihop ad hoc communication. This hop count is essential for calculating the next movement waypoint.

AUVs implement a selective update policy for their brightness tables, retaining only entries that possess superior brightness values compared to their existing records, based on received inter-agent communications. This strategy is critical, as it allows AUVs to rapidly identify and prioritize movement toward spatial regions associated with potentially higher objective function fitness. Such a mechanism is fundamental for facilitating efficient swarm navigation and robust distributed decision-making within the search environment.

At the onset of the search process, the brightness table of each AUV is initialized with a single record: the AUV's own current best found brightness value and its corresponding relative location. This initial entry is continuously refined as the AUV explores the search space and discovers superior locations. The table's population dynamically expands during the communication phase, incorporating new entries received from neighboring AUVs. Furthermore, existing entries are updated selectively if the transmitting AUV subsequently broadcasts a location with a strictly greater (better) brightness value than the currently stored record.

Algorithm 2 Sensing module

procedure SENSING
    brightness ← fitness_function(X)
    if brightness > BT[self.ID].brightness **then**
        BT[self.ID].brightness ← brightness
        BT[self.ID].distance ← 0
        BT[self.ID].angle ← 0
        BT[self.ID].hop ← 0
    end if
end procedure

The brightness table contains a critical hop count record. This hop count metric is essential for two primary functions: first, preparing the subsequent broadcast message for inter-agent communication; and second, calculating the optimal next movement waypoint. Fig. 4 illustrates an instance of the brightness table maintained by AUV D when AUVs A, B, and C are present within the system. Due to a chain of communication propagation, the brightness value originating from A will eventually reach AUV D, requiring three intermediate hops. This specific hop count "3" is precisely the value recorded in AUV D's brightness table entry corresponding to AUV A's best known location.

5.2 Sensing module

Algorithm 2 describes the sensing module in pseudocode. Here, BT represent the brightness table stored in the AUV. Each AUV continuously tracks its own best known brightness value (fitness score). When an AUV discovers a location with a higher fitness, it updates this personal record. At that point, the distance, angle, and hop count are reset to zero, effectively making the AUV's current spot the new local reference for future interactions.

The sensing module's core function is to ensure each AUV accurately maintains this best known brightness value at its current position. This information directly guides the AUV's decisions, including what messages to broadcast and where to move next.

Algorithm 3 Broadcast procedure

```
procedure PrepareMsgToSend()
    msg = {self.ID, 0, 0, self.brightness, 0}
    BestRecord ← GetMaxBrightnes(BT)
    if BestRecord.brightness > self.brightness then
        msg = BestRecord
    end if
    return msg
end procedure

procedure Broadcast()
    msg ← PrepareMsgToSend()
    for each AUV in swarm do
        distance ← ||X_self − X_AUV||
        if distance ≤ TR and AUV ≠ self then
            AUV.receive(self.ID, msg)
        end if
    end for
end procedure
```

Algorithm 4 Receive procedure

```
procedure Receive(senderID, msg)
    senderDistance, senderAngle
                ← IncomingAcousticSignal
    senderPolar ← [senderDistance, senderAngle]
    ID ← msg.ID
    d, a, b ← msg.{distance, angle, brightness}
    hop ← msg.hop + 1
    Polar ← [d, a]
    oldCart ← ToCartesian(Polar)
    senderCart ← ToCartesian(senderPolar)
    totalCart ← oldCart + senderCart
    newPolar ← ToPolar(totalCart)
    oldbrightness ← BT[ID].brightness
    if ID ∉ BT or
            oldbrightness < b then
            BT[ID] ←
                    {newPolar.distance, newPolar.angle,
                    Brightness, hop}
    end if
end procedure
```

5.3 Communication module

The communication module is fundamentally composed of two main procedures: broadcast and receive. This module facilitates the essential inter-agent information exchange within the swarm. During a communication cycle, AUVs selectively broadcast subsets of their brightness table entries to neighboring agents that fall within their defined transmission range. Concurrently, AUVs execute the receive procedure, processing incoming messages from other agents and updating their local brightness tables according to the scheme's update rules. Algorithm 3 provides a detailed description of this module's operation in pseudocode, while the subsequent subsections explain the broadcast and receive procedures in detail.

5.3.1 Broadcast procedure

Prior to transmission, each AUV executes a data selection process to prepare the broadcast message, which contains a subset of its local brightness table. The broadcast procedure employs a filtering criterion where only the best brightness table entry whose recorded brightness value is strictly greater than the AUV's own current brightness is selected. This selective communication strategy is paramount for maximizing communication efficiency by transmitting only the most promising information (i.e., data that indicates a superior solution quality). Consequently, this mechanism effectively reduces communication overhead across the swarm.

Upon message preparation, each AUV transmits the resulting data subset to its neighboring agents. All AUVs operate synchronously on a fixed broadcast cycle, τ_b, initiating transmission every τ_b seconds. The cycle time, τ_b, is configured to be significantly greater than the maximum acoustic signal propagation delay within the operating environment. This configuration ensures that the broadcast message is guaranteed to reach its intended receivers within the cycle duration, assuming no channel loss or physical obstacles.

A message is successfully received by any neighboring AUV located within the transmission range, T_R; agents outside this range are excluded. Upon receipt of a message, the neighboring AUV utilizes the physical layer metrics, specifically the Received Signal Strength Indicator (RSSI) and the Angle of Arrival (AoA) of the incoming acoustic signal, to calculate the sender's relative polar coordinates (distance and angle). These derived polar coordinates, coupled with the received brightness table entries, are then employed to update the receiver's local brightness table in accordance with the AA-FY update rules.

5.3.2 Receive procedure

Upon receiving a message from a neighboring AUV, the receive procedure is immediately invoked to update the local brightness table. This procedure processes each entry in the received message, which contains the neighbor's relative distance, angle, and the associated brightness value. A crucial initial step is the increment of the hop count for the received entry by 1. A correct hop count is essential for calculating the next waypoint in the movement module.

To correctly incorporate the positional information, the AUV first transforms the received polar coordinates into

Algorithm 5 Next waypoint setting procedure

procedure NextWaypoint()
  $polarList \leftarrow [\,]$
  $brightnessList \leftarrow [\,]$
  for each $name$ **in** BT **do**
    $b, d, a \leftarrow BT[name].\{brightness, distance, angle\}$
    $h \leftarrow BT[name].hop$
    $b \leftarrow b \cdot \delta^h$
    if $d \neq 0$ **and** $b > self.brightness$ **then**
      Append $[d, a]$ to $polarList$
      Append $b - self.brightness$ to $brightnessList$
    end if
  end for
  $maxIndex \leftarrow IndexOfMax(brightnessList)$
  $chosen \leftarrow polarList[maxIndex]$
  $newPos \leftarrow$ ToCartesian($chosen$)
  $newPos \leftarrow$ KeepInBounds($newPos$)
  $self.waypoint \leftarrow newPos$
end procedure

Algorithm 6 Moving procedure

procedure Move()
  $dist \leftarrow ||self.X - self.waypoint||$
  if $dist \leq \epsilon$ **then**
    NextWaypoint()
  else
    $dir \leftarrow self.waypoint - self.X$
    $newPos \leftarrow self.X + speed \cdot \frac{dir}{||dir||}$
    for each ID **in** BT **do**
      $polar \leftarrow BT[ID].\{distance, angle\}$
      $neighbor \leftarrow$ ToCartesian($polar$)
      $newPolar \leftarrow$ ToPolar($neighbor, newPos$)
      $BT[ID].distance \leftarrow newPolar.distance$
      $BT[ID].angle \leftarrow newPolar.angle$
    end for
    $self.X \leftarrow newPos$
  end if
end procedure

local Cartesian coordinates. It then computes the entry's relative position with respect to the receiver's own frame of reference. This spatial transformation allows the receiving agent to accurately infer the physical location and quality of the neighbor's information. The brightness table is then selectively updated only if the processed entry is either new or if it contains a superior brightness value compared to an existing record for the same AUV. This selective update mechanism is vital, as it ensures each AUV retains only the most promising positional cues from its neighborhood, thereby promoting effective and decentralized navigation toward high fitness regions of the search space.

5.4 Movement module

The movement behavior of each AUV is governed by two interconnected procedures: nextWaypoint and move. Collectively, these procedures implement the adaptive navigation strategy, determining both when the AUV should relocate (via move) and where the AUV should target its next position (via nextWaypoint), based on the localized intelligence within its brightness table. Crucially, the information stored in the brightness table is continuously and dynamically adjusted throughout the execution of this movement process to maintain accurate relative positioning.

5.4.1 Next waypoint setting procedure

The nextWaypoint procedure dictates the mechanism by which each AUV selects its subsequent target location. An AUV initiates this process by iterating through its local brightness table to identify entries corresponding to other AUVs that possess both a superior brightness value and a non-zero relative distance.

The identified brightness value, s, is then modified by an attenuation factor based on the record's hop count, hop, via the equation $s = s \cdot \delta^{hop}$. The term δ, the light absorption coefficient (where $0 < \delta < 1$), serves an analogous function to the light absorption coefficient γ in the original firefly algorithm. The hop count, hop, quantifies the number of communication relays required for the brightness record to propagate from its source AUV.

Crucially, a higher hop count signifies a greater distance between the current AUV and the location where the brightness value was discovered. Consequently, the exponential attenuation factor δ^{hop} ensures that more distant brightness records have a proportionally diminished influence on the movement decision. This design principle facilitates localized convergence, compelling AUVs to prioritize movement toward nearer, higher quality targets rather than being attracted by distant AUVs, thereby promoting efficient swarm coverage and exploration.

Following the modification of the brightness values based on their respective hop counts, the differences between the current AUV's best known brightness and the attenuated brightness values of the candidates are computed. These differences are subsequently stored and utilized as relative weights to quantitatively gauge the importance of each potential candidate waypoint. From this weighted set of candidates, the AUV employs a greedy selection strategy, choosing the single candidate that corresponds to the maximum weight to calculate its next movement waypoint.

5.4.2 Moving procedure

The move procedure governs the AUV's navigation by determining whether a physical movement is executed or a new waypoint calculation is initiated. Specifically, the procedure evaluates the distance between the AUV's current location and its designated waypoint. If this distance falls below a predefined tolerance threshold, ϵ (i.e., the AUV is deemed sufficiently close to the waypoint), the AUV transitions to the waypoint selection phase to compute a new target location. Otherwise, the AUV advances towards its current waypoint at a constant, predefined speed until the threshold condition is met.

Similar to the receive procedure, all AUV positions recorded within the brightness table are dynamically updated throughout the movement phase. The Cartesian coordinates of other known AUVs must be recalculated relative to the current AUV's new position and subsequently transformed back into polar coordinates. This continuous geometric transformation ensures that the specific location where each brightness value was recorded is accurately maintained, irrespective of the AUV's movement. Crucially, this movement module enables AUVs to execute decentralized, adaptive, and target-oriented navigation decisions within the collective swarm environment.

6. EVALUATION

The mission of the AA-FY system is to search and allocate an AUV swarm to multiple targets in large areas with the help of multihop ad hoc underwater communication. The evaluation of AA-FY will focus on the completeness (or the effectiveness) of the mission. In this section, rigorous assessments on the capacity of the proposed AA-FY scheme with comparisons to MFA will be presented. The successes of AA-FY in locating targets, where there is no assistance from any localization system nor knowledge of initial locations, and allocating AUVs among multiple search targets are evaluated using a range of variable environmental settings.

6.1 Evaluation configurations

The primary purpose of this evaluation is to rigorously assess the capacity of the proposed AA-FY scheme to enable the AUV swarm to successfully locate and allocate themselves across multiple search targets under a range of variable environmental settings, including without the prior knowledge of initial locations, nor the existence of a localization system for location updates. To set as a comparison, the algorithm MFA described in Section 3 is also examined using the same scenario as AA-FY. The major difference between MFA and AA-FY is that MFA does not have the multihop communication capability, thus a brightness value is only known to the immediate neighbors.

The results of these experiments are measured by the allocation of AUVs around the targets, i.e., the numbers of AUVs converged to each target. The more targets being located by the distributed AUVs, the higher the ability AA-FY or MFA handling the multi-target situations. The numbers of AUVs allocated at each target also suggest the ability to spread AUV resources across multiple targets, hence the usefulness of the method. These results are reported using visual demonstration as examples in Fig. 5. Three distinct contour maps are generated for each of the four experimental settings:

1. *Initial state map*: Depicts the scenario when the AUVs are first deployed, prior to the initiation of the search and allocation process.
2. *MFA final outcome map*: Illustrates the final distribution of AUVs achieved by the MFA, serving as a benchmark comparison.
3. *AA-FY final outcome map*: Displays the final distribution achieved by the proposed AA-FY scheme.

These comparative visualizations allow for a clear, qualitative assessment of the effectiveness of the AA-FY scheme relative to the benchmark.

The evaluations are performed in a simulated environment for the specific multi-target scenario. All experiments are conducted in a two-dimensional search space of $1000m \times 1000m$ square meters. Multiple targets are placed in the space. They are represented by a composite fitness contour landscape. To simulate an environment with multiple targets, the fitness function is constructed by combining several inverted Easom functions. In the contour map, e.g., Fig. 5, each target has its own sphere of influence represented by multiple layers of concentric circles. The bright yellow color represents the center of the search target and the purple color indicates no significant signal generated by the target can be detected. There will also be 100 AUVs initially deployed randomly on a 10*10 grid in the space. The AUVs are represented by the blue dots on the map.

The communication range of the AUVs is set to be 150 meters. Meanwhile, the distance between two adjacent AUVs is around 100 m. This range is used to make sure that a specific AUV can only talk to eight adjacent neighbors initially, yet when moving, ad hoc networking still persists. The other related parameters are given in Table 1.

The rest of this section presents the evaluations in four different scenarios. They consider different numbers of targets, different placements of them, and different significance levels. The first scenario is to validate whether

Table 1 – AA-FY simulation parameters setting

Parameter	Value
N	100
τ_s	1 s
v	1.543 m/s
τ_c	5 s
ϵ	5 m
δ	0.7
$T_R(AA-FY)$	150 m
$T_R(MFA)$	300 m

AA-FY indeed works on multiple searching targets, so to show aiding by an ad hoc network is a unique feature of AA-FY. The next three scenarios are to evaluate whether an ad hoc network is truly helpful when allocating the AUVs. The second scenario is to test whether AA-FY can deal with the case where the targets are far apart from each other; the third scenario is for the case that targets are unevenly placed on a certain section of the search space; and the fourth scenario is to test the case where the targets have different significances.

6.2 AUV allocation on multiple targets

The first experiment is to validate that the proposed AA-FY scheme can indeed instruct AUVs to allocate to multiple targets. Here, nine different targets with the same significance are set up in the search space. The targets are also distributed on a grid area. The results are shown in Fig. 5. Like MFA, AA-FY can also distribute AUVs to the nine targets. The difference with MFA is that MFA is still a centralized algorithm. It organized the movement of the firefly with a grand view of their brightness and location status. Meanwhile, AA-FY purely relies on the multihopped ad hoc communication and individual AUV behaviors. The decentralized characteristic of AA-FY does not compromise its allocation capability.

6.3 AUV allocation on targets that are far apart

The second scenario is to test whether the multihop communication feature of AA-FY can truly guide the AUVs located two targets that are apart to their desired destination. As discussed in Section 3, due to the limited communication range, only the AUVs that are near a search target can be attracted by it. Fig. 6b shows that not all AUVs can successfully move to the targets. But with the help of multihop communication, all the AUVs can successfully move to one of the two targets, as Fig. 6c shows. This further proves the necessity of the multihop ad hoc communication for the AUVs' allocation and distribution.

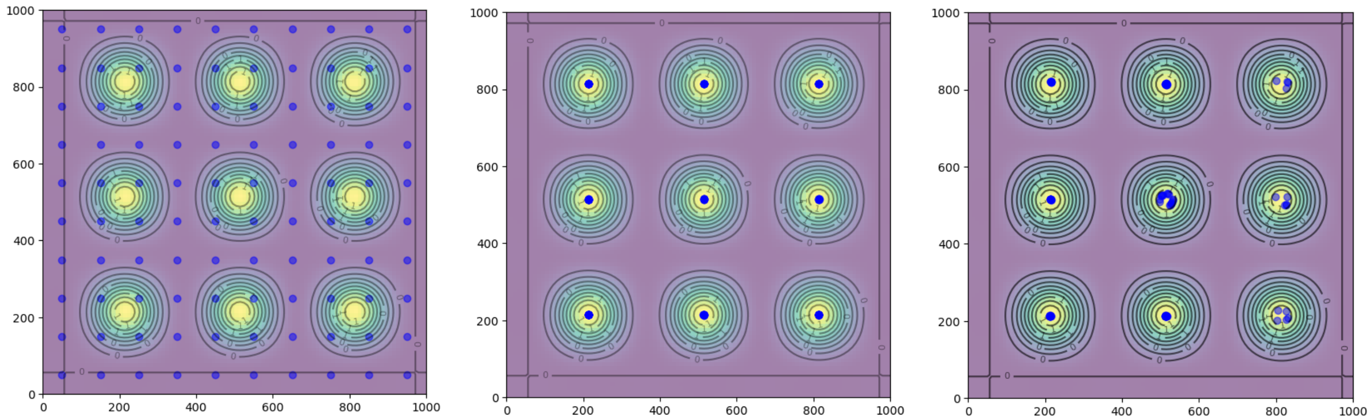
6.4 AUV allocation on biasedly-located targets

Unlike the first scenario, in the third scenario the search targets are no longer evenly distributed in the whole search area. Here, three targets are located at the upper right corner of the search area. This scenario poses a similar challenge to the second scenario. As Fig. 7b shows, without the ad hoc communication, the AUVs located on the bottom left part of the search area have no clue about the existence of the three search targets on the upper right. Hence, not all of the AUVs can move to the area where targets are located. AA-FY, in Fig. 7c, can successfully lead the AUVs to move to the upper right area. We also observed that the target closest to the top right corner of the search space attracted far fewer AUVs compared with the other two targets. Only 10 out of 100 AUVs can reach this target. The reason is that when AUVs on the lower left section of the search space start to move toward the upper right, there is a high chance they will be attracted to the other two targets first. Thus, they are less likely to reach the top right corner.

To rigorously validate the empirical performance of the AA-FY scheme, the evaluation includes an analysis of the experiments detailed in sections 6.2 through 6.4, summarized in Table 2. This table reports the aggregated results across 30 independent simulation runs, detailing both the mean and standard deviation of the MFA and AA-FY scheme to establish the statistical reliability of the swarm's target allocation. It is important to note that, unlike the scenario presented in Table 3, the multiple search targets evaluated in Table 2 possess uniform significance levels across the search space.

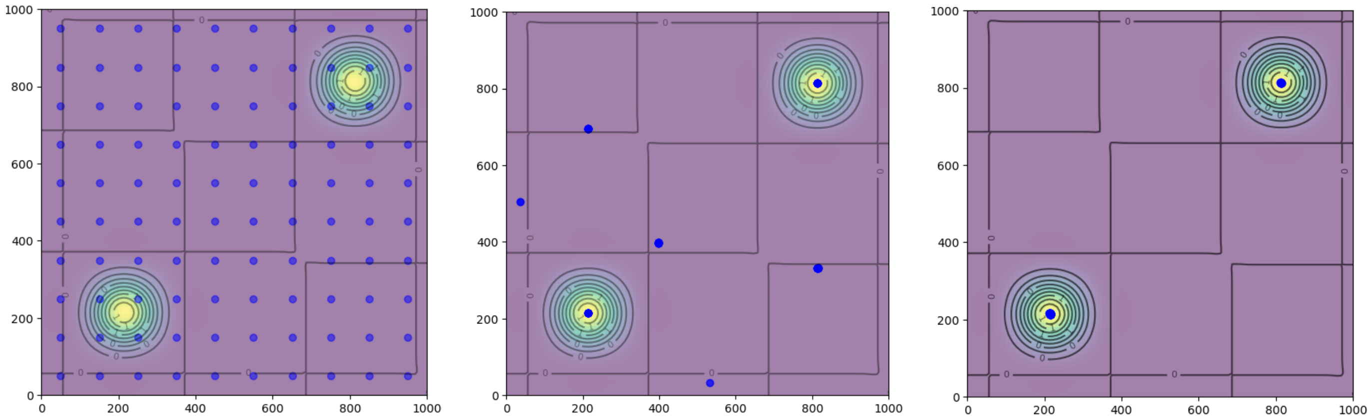
6.5 AUV allocation on targets with various significance

In the previous three evaluations, we assume all the targets have the same level of significance. However, in real underwater scenarios, not all search targets are equal. Taking seabed mining as an example, not all regions have the same mineral concentration level. Logically, the allocation scheme should assign more workforce into the area with a higher mineral concentration level. In this subsection, we would like to see whether the proposed AA-FY scheme can dynamically adjust the allocation when the significance levels of the targets are different. To test this, the fitness function here is constructed by combining four inverted Easom functions. This creates four distinct peaks in the landscape at known locations. One peak represents a high priority target with 100% signal strength, while the other three represent secondary targets, each with 70% signal strength. The precise locations of these four peaks are:



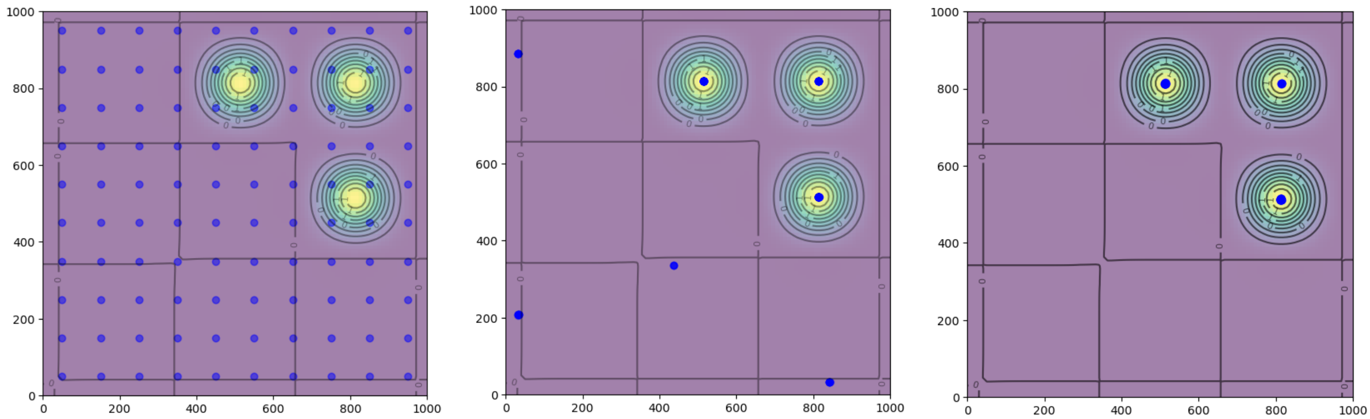
(a) Initial Deployment **(b)** MFA's Distribution **(c)** AA-FY's Distribution

Figure 5 – AUV allocation results on nine targets



(a) Initial Deployment **(b)** MFA's Distribution **(c)** AA-FY's Distribution

Figure 6 – AUV allocation results on two targets that are far apart



(a) Initial Deployment **(b)** MFA's Distribution **(c)** AA-FY's Distribution

Figure 7 – AUV allocation results on three biasedly-located targets

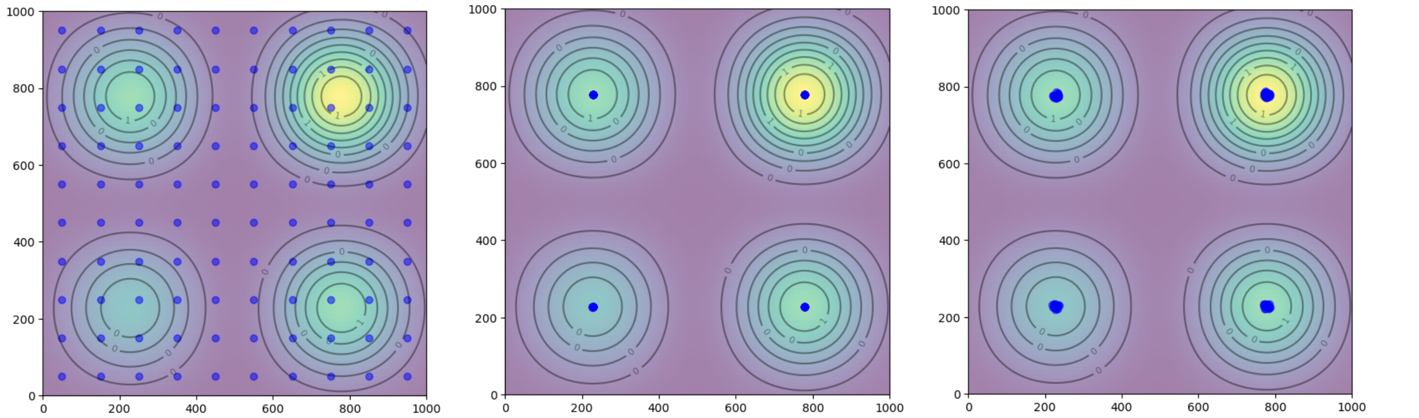
- **Target 1 (100% strength):** at approximately (728, 728)
- **Target 2 (70% strength):** at approximately (228, 228)
- **Target 3 (70% strength):** at approximately (228, 728)
- **Target 4 (50% strength):** at approximately (728, 228)

A visualization of the fitness landscape and the initial deployment of the AUVs is shown in Fig. 8a.

Across all 30 independent runs, our AA-FY successfully allocated the AUVs into distinct clusters around all four targets. The final distribution of the swarm from a representative simulation run is shown in Fig. 8c. The AUVs correctly identify all search targets in the landscape and form stable groups, with a visibly larger group at the high priority target.

Table 2 – AUV mean allocations on targets with same significant levels (averaged over 30 runs)

Scenario	Ideal Allocation	MFA Mean	MFA std	AA-FY Mean	AA-FY std
9 Targets	11.1	11.1	2.2	11.1	6.5
2 Far Apart Targets	50	18.4	2.4	50	9.9
3 Biasedly Located Targets	33.3	25.3	9.5	33.3	20.3



(a) Initial Deployment **(b)** MFA's Distribution **(c)** AA-FY's Distribution

Figure 8 – AUV allocation results on four targets with different signal strength

To quantify this observation, we measured the number of AUVs allocated to each target at the end of each run. Table 3 compares the average allocation over 30 runs to the theoretical ideal. We compared the allocation of the AA-FY and MFA to the ideal allocation. The ideal allocation is calculated based on the proportion of the targets' signal strength level. Here, we record the mean allocation and the miss rate of both MFA and AA-FY. The miss rate is calculated in the following way:

$$(MeanAllocation - IdealAllocation)/IdealAllocation * 100\%$$

The results show that AA-FY's mean allocation is closer to the ideal proportional distribution compared with MAF's allocation. MFA evenly distributed the 100 AUVs to the four search targets, disregarding the different significance of these four targets. The reason is that MFA does not have the support from ad hoc communication. The AUVs initially located on the boundary of the targets' sphere of influence can only move to the target that is strictly closer to them while ignoring the targets' significance level. Since the four targets are evenly distributed at the four quarters of the search space, MFA will also evenly distributed AUVs to them as the consequence.

The results confirm that a complex, system-level task like proportional allocation can be achieved using simple, local rules. The success of AA-FY hinges on two key modifications. First, the hop-based brightness adjustment is critical for niching. It prevents AUVs from being influenced by distant, high-strength targets, forcing them to explore and converge upon their local peaks. This naturally partitions the swarm into subgroups. At the same time, unlike an absolute partition, the message sent by the AUVs located at the most significant target may attract a few more AUVs at the interval of the targets. Hence, unlike the even distribution of the MFA allocation, the target with a higher significance has the potential to attract more AUVs.

The significance of these evaluation results is that they prove that AA-FY is a robust, decentralized strategy for multi-target missions. The AUVs do not need a central controller or a map of the environment to perform their task. This decentralized nature makes the swarm resilient to individual AUV failures and suitable for missions in unknown territories where communication with a central command is hardly possible. The behavior is emergent, arising from the local interactions of the agents themselves.

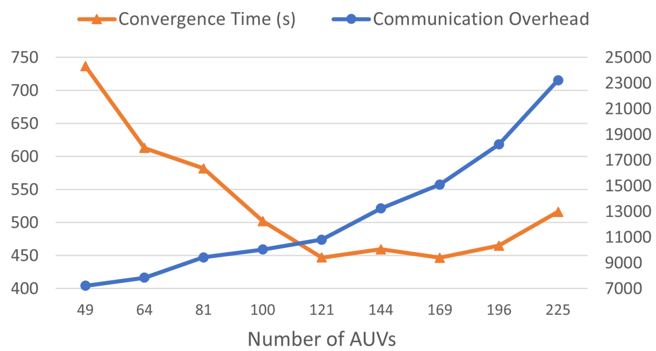


Figure 9 – Convergence time and communication overhead against amount of AUVs

Table 3 – AUV mean allocations on four targets with different significant levels (averaged over 30 runs)

Target	Ideal Allocation	MFA Mean	MFA Miss Rate	AA-FY Mean	AA-FY Miss Rate
Target 1 (100%)	35	25.8	-26.3%	32.7	-6.6%
Target 2 (70%)	24	24.3	1.3%	24.2	0.8%
Target 3 (70%)	24	25.3	5.4%	22.9	-4.6%
Target 4 (50%)	17	24.6	44.7%	20.2	18.9%

6.6 Scalability

To comprehensively evaluate the scalability of the AA-FY scheme, this subsection analyzes system performance across varying AUV population sizes ($N \in \{49, 64, \ldots, 225\}$). The reason we used square numbers is because of our squared grid deployment strategy. Using a square number can ensure the number of the AUVs on a row or column of the grid remains the same. This uniform pattern is good for ad hoc connections. Performance is evaluated based on two primary metrics: convergence time (measured in seconds) and communication overhead (quantified as the total number of broadcast messages generated by the swarm over the simulation's duration).

Empirical results are shown in Fig. 9. This figure reveals a non-linear relationship between swarm size and convergence efficiency. Smaller population sizes result in prolonged convergence times, which is attributed to the increased average inter-agent distance hindering the formation of a fully connected ad hoc network and delaying information dissemination. Conversely, deploying an excessively large population also degrades convergence performance. In highly dense swarms, the corresponding surge in communication overhead significantly increases the probability of packet collisions within the shared acoustic channel, thereby impeding the efficient propagation of optimal target locations.

7. CONCLUSION

This paper introduces the Ad hoc network Assisted Firefly system (AA-FY), centered at a novel, decentralized algorithm to solve the multi-target task allocation problem for AUV swarms in underwater search missions, where standard swarm algorithms like the firefly algorithm may fail due to large search areas and no infrastructure support. AA-FY overcomes this by using multihop ad hoc communication and a hop-based brightness attenuation. This mechanism forces AUVs to prioritize local targets, enabling the swarm to form stable "niches" around multiple objectives. Evaluations demonstrated that AA-FY successfully guides all AUVs to targets, even when they are far apart or clustered, a task where the simpler MFA failed. Most importantly, AA-FY achieves proportional allocation, distributing the AUVs according to the signal strength of each target. The results confirm that complex, robust, and resilient swarm behavior can emerge from simple, local interaction rules without a central controller. In the future, we plan to integrate other nature-inspired swarming schemes, such as the virtual force algorithm, to further improve the allocation methods so that the attention received by the targets can be more evenly distributed.

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