Multilevel Coalition Formation Strategy for Suppression of Enemy Air Defenses Missions

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This paper investigates the problem of how to form coalitions in teams of heterogeneous vehicles. In particular, a coordination strategy is designed for unmanned vehicles to autonomously carry out the suppression of enemy air defenses (SEAD) mission, which would benefit from a heterogeneous network of unmanned vehicles to search and destroy threats in an unexplored area. Inspiration for this work is drawn from natural systems, and we consider the alliance-forming behavior of bottlenose dolphins as a guiding example. A two-phased approach is taken to develop the bioinspired strategy. First, in the context of multi-agent systems, a mathematical model is produced that expresses the alliance-forming behavior. Next, this model is tailored to the suppression of enemy air defenses mission: the target application. Advantages of using this bioinspired approach are discussed and simulations are provided to demonstrate its operation.

Nomenclature

$\mathcal{A}$ = coordinate set of areas to be explored by high-altitude unmanned aerial vehicles
$\mathcal{A}_r$ = coordinate set of areas within $\mathcal{A}$ to be explored by medium-altitude unmanned aerial vehicles
$\mathcal{C}$ = $\{c_1, \ldots, c_N\}$, set of all combat unmanned aerial vehicles
$\mathcal{G}(V, E)$ = graph on vertex set $V$, with edge set $E \subseteq V \times V$
$I$ = $\{h_1, \ldots, h_N\}$, set of all high-altitude unmanned aerial vehicles
$I_1$ = $I_1 \in I_1$, ordered set of all combat pairs
$I_2$ = $I_2 \in I_2$, ordered set of all combat triplets
$M$ = $\{m_1, \ldots, m_N\}$, set of all medium-altitude unmanned aerial vehicles
$N_i$ = neighborhood set of vehicle $i$ (those who can communicate with $i$)
$r$ = transition rule from one subgraph to another subgraph
$S_1$ = ordered set of all higher-order teams of size 4
$S_2$ = ordered set of all higher-order teams of size 5
$t$ = time, s
$\Sigma$ = vertex label set
$\Phi$ = set of transition rules on subgraphs

I. Introduction

An increasing number of applications involving engineered systems currently require the services of a network of unmanned vehicles. A significant advantage of deploying a network of vehicles, instead of relying on a single vehicle, is that it lends itself to the possible cooperation among vehicles. To perform certain tasks, due to the limited capabilities (sensing, computational) of unmanned vehicles, it is often necessary to build competent teams of these vehicles, where vehicles can cooperate with team members to use complementary capabilities or provide support/coverage for other team members. For example, combat vehicles responsible for destroying targets can benefit by approaching the targets as a group, in a coordinated manner, to confuse the target's radar systems [1]. There are also applications that require teams of vehicles to cooperate with other teams, thus gaining a higher degree of coordination among the vehicles in the network. An example of such an application is a mission involving autonomous, unmanned vehicles as attacks on enemy defenses (SEAD) mission [2]. In short, the success of this U.S. Navy mission depends on satisfactory reconnaissance, targeting, and elimination of threats, which makes the design of an effective coordination strategy imperative. In this paper, we develop a coordination strategy for a network of autonomous, unmanned vehicles performing the SEAD mission.

The objective of the SEAD mission, conceptualized in [2], is to search and neutralize threats in an unexplored area using unmanned vehicles. The mission involves a heterogeneous network of vehicles, where heterogeneity arises from the difference in functionalities of each type of vehicle in the network. There are three types of vehicles: two types of surveillance vehicles, and combat vehicles. To search for threats, the surveillance vehicles cooperate in teams known as intelligence, surveillance, and reconnaissance (ISR) teams. Each ISR team consists of a pair of vehicles, a high-altitude and -endurance (HAE) unmanned aerial vehicle (UAV) and a medium-altitude and -endurance (MAE) UAV. The idea is to let the higher-altitude detector vehicle ‘cue’ a lower-altitude examiner vehicle for accurate identification of threats. Thus, the two vehicles in an ISR team...
cooperate to achieve ‘final target confirmation’ [2]. The information about the threat (e.g., nature, location) is passed on to another team of vehicles, the combat teams. The combat teams consist of uninhabited combat air vehicles (UCAVs), and these vehicles operate in teams to effectively eliminate threats. One such team is illustrated in Fig. 1.

As a purely strategic coordination problem, the challenge is to autonomously build multilevel coalitions of vehicles for a heterogeneous network. On a lower-level, vehicles form ISR and combat teams, and on a higher-level, ISR teams coordinate with combat teams to eliminate threats. In fact, this particular set up of the SEAD mission, using a heterogeneous network of vehicles, is what distinguishes our work from previous works done by other researchers related to the coordination of vehicles during suppression missions (for a representative sample, see [3–7]).

Previous research efforts focused only on the combat aspects of the SEAD mission, and problems such as task allocation and path finding are addressed for a network of UCAVs. More generally, target elimination using multiple vehicles has been addressed by Arslan et al. [8] and Beard et al. [1]. In [8], a game-theoretic negotiation policy is developed that assigns vehicles to targets. A utility function is designed so that locally interacting vehicles of identical type meet a global performances criterion. In [1] and [9], vehicles are assigned to known target locations, and the subproblems addressed in these works include target assignment, path planning, and trajectory following. Our focus is on building teams, and previous works that have addressed this problem (i.e., coalition formation) either use a centralized approach by deploying an auctioneer agent or incorporate game-theoretic methods, where a vehicle’s utility often requires information about all other vehicles in the network (for a representative sample of coalition-formation algorithms, see [10–15]).

Our contribution is to present a decentralized, multilevel coalition-formation algorithm scalable to very large number of vehicles. This method is robust to failures and potential vehicle losses by letting coalitions form or dissolve dynamically. Such a decentralized and robust algorithm is essential to SEAD operations where very large number of UAVs collaborate to locate and neutralize multiple mobile enemy air defence assets in a relatively short time.

This algorithm, compared to centralized methods discussed earlier, is not optimal. However, allowing only local information available to each UAV to drive the coalition formation, it is robust to failures (vehicles themselves or communication links) and easily scalable to very large number of vehicle, two characteristics that a large-scale autonomous SEAD mission desires but lacks in centralized team-building methods.

Because of the nature of the SEAD mission, assuming that each vehicle can keep track of all other vehicles deployed in the area is not a feasible assumption. Moreover, we want to design a decentralized strategy so that vehicles can continue the mission despite the loss of any other vehicle in the network. Thus, we require a coordination strategy where each agent in the network autonomously makes decisions based on local information. Furthermore, we turn to nature for inspiration to develop the coordination strategy, and this specific choice in its design stems from the fact that many biological systems solve complex tasks in a decentralized, robust, and scalable manner (see [16–19] for examples of such biological systems). These are characteristics that are desirable for the engineering application addressed in this paper (see [20,21] for examples of other applications where these characteristics are exploited) and, more specifically, let the multilevel alliance-forming behavior of dolphins guide the design of the coordination strategy. The approach to bioinspiration presented here is two-phased. First, a model of bottlenose dolphin alliances is presented; next, this model is tailored for the SEAD mission to produce the targeted coordination strategy.

The remainder of this paper is organized as follows. In Sec. II, we briefly discuss dolphin alliances and present a mathematical model that expressively captures this behavior. In Sec. III, we present the preliminaries of the problem, and in Sec. IV we design the bioinspired coalition strategy to build multilevel coalitions. Simulations of the strategy are shown in Sec. V, and conclusions are presented in Sec. VI.

II. Bioinspiration

Success of SEAD-type missions depends on the timely allocation of assets in a decentralized manner. The general coalition formation problem is computationally complex and, as such, effective yet suboptimal solutions are needed. One way in which such solutions can be obtained is to look for already-existing natural solutions. For instance, there are examples of biological systems where social activities include buildings teams of individuals to compete for resources. These activities are analogous to the operation of the SEAD mission and, as a result, we borrow design principles from nature to guide the interaction rules among vehicles. In particular, the coordination strategies are based on the social behavior of bottlenose dolphins, and in subsequent sections we will show that this inspiration leads to a reasonable design solution to the SEAD mission, where the resulting coordination strategy is robust and decentralized.

Bottlenose dolphins are considered as intelligent, social animals, and their highly coordinated activities, which includes many elaborate techniques to catch prey, have been well documented (see [22–25]). In this work, we are interested in the social behavior of forming alliances, and as such, in this section, we begin with a brief description of dolphin alliances and then present a mathematical model that expressively captures this biological behavior. We developed parts of this model in [26], and the coordination strategy designed for the SEAD mission in Sec. IV is based on the overall framework of the model.
A. Multilevel Coalition Formation of Bottlenose Dolphins

Male bottlenose dolphins form two levels of alliances: first-order and second-order alliances [27]. In short, these alliances are built to increase a male’s chances of mating (for details, see [27–30]). The first-order alliance consists of a pair or triplet of male dolphins, and dolphins are almost always seen together with their first-order alliance members. More formally, they share a high “association coefficient” [27], an indicator of how often two individual dolphins are seen together. Males of a first-level alliance herd female dolphins by swimming in a coordinated manner, and this way they inherently constrict the movement of the elusive females. However, a first-order alliance is incapable of stealing a female dolphin already being herded by another alliance [29]; in such a scenario, dolphins coordinate with each other to build higher-level teams.

Consider the following example scenario, as depicted in Fig. 2a, where three first-order alliances are shown: A, B, and C. Furthermore, alliance C is herding a female, and alliance B is attracted to that female. According to [29], alliance B probably realizes that the outcome of a fight with alliance C is unpredictable because they are both similar-sized alliances. In this case, alliance B will initiate a higher-order team, formally known as a second-order alliance (a cluster of two first-order alliances). In this example, a third alliance, alliance A, accepts alliance B’s request, and their second-order alliance is shown in Fig. 2b. The female is being herded by alliance B, the outcome of the fight between second-order alliance and the smaller first-order alliance (Fig. 2c).

There are two interesting facts related to the formation of higher-order teams:

1) Second-order alliances break immediately after the task is complete.
2) Interactions between first-order alliances can be hostile and favorable.

For a more detailed account of this observation, see [27]; in short, referring to the scenario shown in Fig. 2, alliance A is not guaranteed to assist alliance C. Perceiving a threat from alliance B, alliance C might send a request to alliance A to help defend its female.

B. Mathematical Model of Dolphin Alliances

We modeled the multilevel alliance forming behavior of male bottlenose dolphins in [26]. Using tools from graph theory, hybrid systems, and embedded graph grammars (EGGs), we formalized alliances in the context of multi-agent systems. The model was produced to effectively mimic the underlying biological phenomenon of dolphin alliances, but the simplicity of the model made it amenable to analysis.

The rigorous mathematical definition of the method allows us to draw from the vast library of tools in graph theory and networked systems to present formal conclusions about the robustness and performance of the developed model under certain assumptions [26].

But biology aside, one result of the work was a decentralized coalition-formation algorithm and, according to the algorithm, agents (with limited communication ranges) in the network made decisions using locally available information. Male agents produced clusters of pairs and triplets (first-order alliances), and when a scenario as described in Fig. 2 arose, two clusters combined to form higher-order teams (second-order alliances). The formation of alliances was solely driven by agent-based representations of biological parameters (e.g., familiarity between dolphins). Moreover, the underlying parameter driving the formation of first-order alliances was an agent-based definition of the association coefficient. There, the parameter \( a_{i,j}(t) \) denoted how the association agent \( i \) felt toward agent \( j \) at time \( t \), and a higher association represented a stronger desire to form a coalition. A first-order alliance was either in the search, herd, or idle mode, based on its interaction with female agents in the network. Hence, in the context of multi-agent systems, the alliances were task-oriented, and the objective was to ‘herd a female.’

Consider a vertex-labeled graph, given by the tuple \( G = (V_0, E_0, \phi_0) \), where \( V_0 \) is the set of all agents (male and female), \( E_0 \subset V_0 \times V_0 \) is the set of edges \( (i,j) \in E_0 \) if there is a communication link between agents \( i \) and \( j \), and the function \( \phi_0 \) assigns a label from the label set \( \Sigma_0 \), to the agents in the network. Now, an EGG is a formalism that takes a vertex-labeled graph as an input and produces another vertex-labeled graph as an output, based on a set of rules (for details, see [31]). Furthermore, each rule in the set of transition rules \( \Phi_0 \) is given by a pair \( r = (L \rightarrow R) \), where \( L \) and \( R \) are subgraphs. Also, if the state-dependent guard condition associated with rule \( r \) is true, then the application of the rule \( r \) on the original subgraph \( L \) produces the subgraph \( R \).

The multilevel alliance forming of dolphins was described used 13 rules in [26], and these rules included formation of first-order alliances, herding female agents, and fights between alliances. The formation of a first-order alliance (see Fig. 3) was represented by the following grammar transition rules:

\[
\Phi_0^0 = \begin{cases} 
  \text{w} \rightarrow \text{p} & (r_1), \\
  \text{p} \rightarrow \text{t} & (r_2),
\end{cases}
\]

where \( \Phi_0^0 \in \Phi_0 \). For these two transition rules, the label set is defined as \( \Sigma_0^0 = \{w, p, t\} \), where \( \Sigma_0^0 \in \Sigma_0 \), and \( w, p, \) and \( t \) represent the labels wander, pair, and triplet, respectively. Male agents that are not part of any alliance are labeled \( w \). If the guard condition for \( r_1 \) evaluates to true, then, by applying \( r_1 \) to two wandering agents, a first-order pair is formed, and the two wandering agents are now labeled \( p \). Additionally, if the guard condition for \( r_2 \) evaluates to true, then, by applying rule \( r_2 \) to a first-order pair and a wandering agent, a first-order triplet is produced, where each member of the alliance is labeled \( t \).
The nature of these guard conditions are detailed in [26], but in essence they are driven by agent-based definitions of biological parameters like the association coefficient. In this work, we tailor the model of dolphin alliances to build multilevel vehicle teams, which inherently makes the approach to designing coordination strategies bioinspired. Furthermore, we let vehicle–vehicle interactions be driven by parameters that are related to engineered systems, and in particular, the target application: the SEAD mission.

As mentioned earlier, we use this bioinspired algorithm to achieve multilevel UAV team coalitions. This is a natural choice because this procedure is capable of producing multilevel alliances among agents in a decentralized fashion and is scalable to handle large number of agents in a highly dynamic environment. In subsequent sections, we will set up the SEAD mission and produce multilevel vehicle teams.

III. UAV Exploration Strategies

In this section, we first introduce some notations used in description of UAV teams and interactions among them, and then we discuss the exploration strategy of the surveillance vehicles during the SEAD mission.

A. Notations

The vertex-labeled graph is denoted by $G = (V, E, l, \Sigma)$, where $V$ is the set of all agents in the network (i.e., all vehicles), $E \subset V \times V$ is the set of edges (we assume all vehicles have the identical communication ranges, regardless of vehicle-type), and the function $l$ assigns a label from the label set $\Sigma$ to the agents in the network. Furthermore, the set of transition rules is denoted by $\Phi$. The following are some additional set notations describing groups of HAE UAVs, MAE UAVs, UCAVs, and ISR teams.

1) $H = \{h_1, \ldots, h_{N_H}\}$ is the set of all HAE UAVs.
2) $M = \{m_1, \ldots, m_{N_M}\}$ is the set of all MAE UAVs.
3) $C = \{c_1, \ldots, c_{N_C}\}$ is the set of all UCAVs.
4) $I$ is the ordered set of all ISR teams.
5) $J_1$ is the ordered set of all combat pairs.
6) $J_2$ is the ordered set of all combat triplets.
7) $S_1$ is the ordered set of all higher-order teams of size 4.
8) $S_2$ is the ordered set of all higher-order teams of size 5.

Fig. 3 Simulation of wanderer males ($w$) forming clusters of pairs ($P$) or triplets ($T$), based on a familiarity measure, to herd female agents ($f$). Possession of a female is lost during fights.
9) \( \mathcal{N}_i \) is the neighborhood set of vehicle \( i \), and it contains the vehicles that can communicate with vehicle \( i \).

Thus, the set of all vehicles is given by \( \mathcal{V} = \cup A \cup \mathcal{C} \). Also, each HAE UAV, MAE UAV, and UCAV is initially assigned the label \( h^0 \), \( m^0 \), and \( c^0 \), respectively, and these superscripts denote the fact that, initially, the vehicles are not part of a coalition.

B. Exploration

Let \( A \) be a set of coordinates, and assume that the exploration task is complete once the HAE UAVs have visited these coordinates. The idea is that, by visiting all the coordinates in \( A \) through the detection range of their sensors, the HAE UAVs cover the entire search area. Thus, the information of a subarea, the size corresponding to the sensing range of HAE UAVs, is embedded in the information gathered from the coordinates associated with that subarea and, together, these subareas span the entire search area. When the HAE UAV detects a threat in one of these coordinates, it passes this information to an MAE UAV, more specifically its ISR team member. (An MAE UAV is equipped with a low-resolution imaging capability, and the idea is to let this vehicle alert a slower-moving MAE UAV, which is equipped with a high-resolution imaging capability.)

This MAE UAV is now responsible for combing the subarea, and we assume that there is a set of coordinates associated with each coordinate in \( A \) and, by traversing these coordinates, the subarea is completely explored. We denote \( A'_i \) to be the set of coordinates that must be explored by the MAE UAV in charge of searching the node \( k \in A \) for target confirmation. Furthermore, \( A'_i \cap A'_j = 0 \), \( \forall k, j \in A \), and \( k \neq j \).

Each HAE UAV uses the indicator functions \( h_{\text{explored}}: \times A \to \{0, 1\} \) and \( h_{\text{detect}}: \times A \to \{0, 1\} \) to classify the coordinates in \( A \). The HAE UAV \( i \) will visit an unexplored coordinate \( i \in A \), i.e., \( h_{\text{explored}}(i, k) = 0 \), and if it senses a threat in the area associated with that coordinate, it will set \( h_{\text{detect}}(i, k) = 1 \). Similarly, MAE UAVs use the indicator function \( m_{\text{explored}}: \times A \to \{0, 1\} \), where \( i \in A \), when tasked to search for threats by their ISR team members.

In the next section, we will first specify the rules to form surveillance and combat teams and, subsequently, present rules to form higher-order teams that consist of a combination of the two.

IV. Heterogeneous Unmanned Vehicle Teams

In this section, we begin with rules to form surveillance teams, combat teams, and higher-order teams and conclude this section with a discussion on the computational advantages of deploying the bioinspired strategy.

A. Intelligence, Surveillance, and Reconnaissance Teams

The ISR team is initiated once an HAE UAV detects a threat while traversing the coordinates in \( A \). It requests the nearest MAE UAV, and if this MAE UAV accepts the request, the two vehicles form an ISR team. The formation of an ISR team is represented by the following transition rule:

\[
\Phi^1 = h^0 \rightarrow m^0 \rightarrow h^1 \rightarrow m^1 (r_1)
\]  

(2)

where \( \Phi^1 \in \Phi \), and we define a label set \( \Sigma^1 = \{h^0, m^0, h^1, m^1\} \in \Sigma \). Thus, for two vehicles \( i \) and \( j \), where \( l(i) = h^0 \) and \( l(j) = m^0 \), if the guard condition for \( r_1 \) is true, then the application of rule \( r_1 \) relabels the two vehicles, and the outcomes are \( l(i) = h^1 \), \( l(j) = m^1 \), and \( (i, j) \in \mathcal{T} \). The guard condition associated with \( r_1 \) is true if 1) vehicle \( i \) sends a request to vehicle \( j \), and 2) vehicle \( j \) accepts this request.

The HAE UAV \( i \) will send a request to available MAE UAVs labeled \( m^0 \). MAE UAV \( j \) responds to this request along with its coordinates. In the case that HAE UAV \( i \) receives multiple simultaneous acceptance messages back, it chooses MAE UAV \( j \) to be the nearest vehicle to target point \( \mathcal{H}_i \), where \( h_{\text{detect}}(i, k) = 1 \). We also design a method by which a MAE UAV makes a selection when presented with multiple HAE UAV requests. Let the function \( h_{\text{quality}}(i, k) : \times A \to [0, 1] \) denote the quality of the detection made by HAE UAV \( i \) regarding coordinate \( k \). Consider the MAE UAV \( m \) that simultaneously sends a request to vehicle \( j \), but regarding coordinate \( n \). If \( h_{\text{quality}}(i, k) > h_{\text{quality}}(m, n) \), it implies that there is less uncertainty associated with the possibility of a threat being located in the subarea associated with coordinate \( k \). In this case, according to our model, vehicle \( j \) will accept the request sent by the HAE UAV \( i \). The guard condition for \( r_1 \) evaluates to true, and subsequently, vehicle \( j \) will begin exploring the coordinates in \( \mathcal{A}'_i \). Furthermore, we assume that the HAE UAV initiates a holding pattern over the coordinate \( k \) until it is relabeled to \( h^0 \) (this transition rule is described later). We chose to keep HAE UAV in the coalition and in a holding pattern over the search area until all threats within coordinate \( k \) are neutralized. This holding pattern is to provide perpetual wide area surveillance to monitor for possible popup threats that can jeopardise the mission or provide other services to other UAVs operating in that coordinate. If this support role is not required, it is more efficient to allow the HAE UAV move to other coordinates and continue its role in detecting areas of potential threat.

B. Combat Teams

Although no particular size is specified for combat teams in [2], their advantages are discussed in [1], i.e., multiple combat-capable vehicles that arrive at the target’s location at the same time can confuse the target’s defense system. However, it is conceivable that too many vehicles can deteriorate the group’s ability to coordinate effectively (e.g., [32] addresses the topic of agent-agent interference during retrieval tasks). Based on the model of first-order alliances of dolphins, we restrict the size of combat teams to either pairs or triplets of combat vehicles. The rules for building UCAV teams are as follows:

\[
\Phi^2 = \begin{cases} 
  c^0 \xrightarrow{\phi^0} c^1 \xrightarrow{\phi^1} (r_2), \\
  c^1 \xrightarrow{\phi^1} c^2 \xrightarrow{\phi^2} (r_3).
\end{cases}
\]  

(3)

In Eq. (3), rule set \( \Phi^2 \in \Phi \), and the label set is denoted by \( \Sigma^2 = \{c^0, c^1, c^2\} \in \Sigma \). We assign capabilities to individual UCAVs, and this measure of capability can be thought of as a function of the state of the vehicle. For example, it can be designed as a function of the vehicle’s fuel consumption, onboard weapon systems, and/or health. Let the capability of combat vehicle \( i \) be given by the nonincreasing function \( c_{\text{cap}}(i) \in \mathbb{R} \), and in our model, a UCAV will be available to form a combat team if \( c_{\text{cap}}(i) \geq \xi_i \), where \( \xi_i \) is a positive constant. The idea behind this formulation is that an UCAV must be ‘fit’ in order to join a combat team. Groups are formed when the sum of the individual capabilities of the members reaches a certain threshold, denoted by a positive constant \( \xi_r \), and the capabilities of each member is greater than \( \xi_r \). (Note that this is one example of where the
coordination algorithm, when compared to the algorithm of [26], has moved away from biological parameters to ones pertaining to artificial systems.)

When the guard condition of \( r_2 \) is true, for two vehicles \( i \) and \( j \) labeled \( c^0 \), the outcome of applying \( r_2 \) is the formation of a combat pair - (i, j) ∈ \( \mathcal{J}_1 \), \( l(i) = c^1 \), and \( l(j) = c^1 \). The guard condition of \( r_2 \) is true if \( c.\text{cap}(i) \geq \xi_i \), \( c.\text{cap}(j) \geq \xi_j \), and \( c.\text{cap}(i) + c.\text{cap}(j) \geq \xi \). A triplet is formed through the addition of an agent to an existing pair. Thus, for three agents, \( i, j, \) and \( k \), where \( (i, j) \in \mathcal{J}_1 \), \( l(i) = c^1 \), \( l(j) = c^1 \), and \( l(k) = c^0 \), then the application of \( r_1 \) forms the triplet \( (i, j, k) \), where \( (i, j, k) \in \mathcal{J}_2 \), \( l(i) = c^2 \), \( l(j) = c^2 \), and \( l(k) = c^2 \). The guard condition of \( r_3 \) is true if \( c.\text{cap}(i) \geq \xi_i \), \( c.\text{cap}(j) \geq \xi_j \), \( c.\text{cap}(k) \geq \xi_k \), and \( c.\text{cap}(i) + c.\text{cap}(j) + c.\text{cap}(k) \geq \xi \).

In the simulations shown in Sec. V, the capability of combat vehicles corresponds to onboard weapon systems. Following the neutralization of a threat, the capability of the members in the combat group decreases. Also, in our setup, the threshold \( \xi \) is chosen in such a way that any UCAV team is capable of neutralizing at least one threat.

The breakdown of a combat team can be described by the following rules:

\[
\Phi^3 = \begin{cases} 
  c^3 \rightarrow c^1 \rightarrow c^0 \rightarrow c^0 \ (r_4), \\
  c^2 \rightarrow c^2 \rightarrow c^0 \rightarrow c^0 \ (r_5).
\end{cases}
\]

The rules \( r_4 \) and \( r_5 \) have the same guard condition, which evaluates to true when either the capability of at least one vehicle in the combat team drops below \( \xi \) or the sum of the capabilities drops below \( \epsilon \xi \). Note that, when capability of one of the vehicles in a combat team drops below \( \xi \), this vehicle can no longer join a combat team and will head back to the base to refuel or to receive needed weapon systems. The rest of the dissolved team can almost immediately form a new coalition among themselves or with other available combat UAVs as long as their individual and total capabilities are above the \( \xi \) and \( \epsilon \xi \), respectively.

C. Higher-Order Teams

Consider an ISR pair searching the coordinate \( k \in \mathcal{A} \). While the MAE UAV visits all the coordinates in \( \mathcal{A}_i \), the HAE UAV maintains a holding pattern around coordinate \( k \). After the MAE UAV completes its exploration, it shares the number of targets identified with its ISR member. We denote the number of targets by \( m.\text{num}(i, k) \), where \( m.\text{num}: \mathcal{M} \times \mathcal{A} \rightarrow \mathbb{N} \) describes the number of targets identified by MAE UAV \( i \) after exploring all the coordinates in \( \mathcal{A}_i \). If at least one target is detected, both members of the ISR team initiate a request to form a higher-order team.

It can become quite cumbersome to express transition rules involving teams of vehicles because, for a given team, all possible interactions with each team member must be explicitly denoted. Instead, we effectively use a shorthand by introducing artificial labels, which are not part of the label set \( \Sigma \). We introduce an artificial label set \( \sigma^1 = \{ I, J_1, J_2 \} \), where \( I \), \( J_1 \), and \( J_2 \) represent the ISR team, the combat pair, and the combat triplet, respectively. Here, the artificial label \( I \) encodes a pair of ISR members, i.e., the two vehicles represented by \( I \) are labeled \( h^1 \) and \( m^1 \) in the graph \( G \). Similarly, \( J_1 \) encodes a combat pair (vehicles are labeled \( c^1 \)); \( J_2 \) encodes a combat triplet (vehicle are labeled \( c^2 \)). As an example, consider the interaction between an ISR team, artificially labeled by \( I \), and agent \( i \). There are three possible scenarios that capture this interaction, and these scenarios are illustrated by Fig. 4.

With this shorthand, the rules for building higher-order teams are presented next:

\[
\Phi^4 = \begin{cases} 
  I \rightarrow J_1 \rightarrow I^1 \rightarrow J_1^1 (r_5), \\
  I \rightarrow J_2 \rightarrow I^1 \rightarrow J_2^1 (r_6)
\end{cases}
\]

where \( \Phi^4 \in \Phi \), and we introduce labels from the artificial label set \( \sigma^2 = \{ I^1, J_1^1, J_2^1, J_1^2, J_2^2 \} \); the superscripts refer to the size of the resulting higher-order team. In the graph \( G \), the outcome of applying \( r_6 \) is a relabeling of the HAE UAV, MAE UAV, and the combat vehicles to \( h^2 \), \( m^2 \), and \( c^3 \), respectively. Similarly, the outcome of applying \( r_5 \), is a relabeling of the HAE UAV, MAE UAV, and the combat vehicles to \( h^1 \), \( m^4 \), and \( c^4 \), respectively. With this rule, we also define a label set \( \Sigma^1 = \{ h^1, m^1, c^1; h^2, m^2, c^3; h^3, m^3, c^4 \} \in \Sigma \).

The guard condition of \( r_6 \) evaluates to true, if the combat team \( (m, n) \in \mathcal{J}_1 \) accepts the request sent by the ISR team \((i, j) \in \mathcal{I} \). When a threat is detected, i.e., \( m.\text{num}(j, k) > 0 \), where \( k \in \mathcal{A} \), the ISR team sends a coalition request including the position of the threat to be cleared to available combat teams (labeled \( J_1 \) and \( J_2 \)). The combat team responds with ID and position of all combat team members. In case that the combat team receives more than one request, it responds to the one that threats is cleared is closest to the centroid of the combat team. Similarly if the ISR team receives more than one response, it will choose the team closest to the threat. Because each member in a team knows the ID of the other team members, there is no need for a leader. Communications can be handled by any of the team members as long as they share this information with their team members. Given a choice between two combat teams, according to this model, the ISR team prefers the larger team. The team size can be inferred from the cardinality of the team ID set received. The combat team accepts this request if it is available, i.e., \((m, n) \notin S_1 \). Thus, for four
vehicles $i, j, m,$ and $n$, where $l(i) = h^1, l(j) = m^1, l(m) = c^1, l(n) = c^1$, and $(i, j) \in \mathcal{I}, (m, n) \in J_1$, the application of $r_6$ yields $(i, j, m, n) \in S_1$ and the vehicles are relabeled as follows: $l(i) = h^2, l(j) = m^2, l(n) = c^2$, and $l(n) = c^2$.

The guard condition for $r_7$ evaluates to true if the combat team $(m, n, o)$ accepts the request sent by the ISR team $(i, j)$. For the vehicles $i, j, m, n,$ and $o$, where $l(i) = h^1, l(j) = m^1, l(m) = c^1, l(n) = c^2, l(o) = c^2$, and $(i, j) \in \mathcal{I}, (m, n, o) \in J_2$, the application of $r_8$ yields $(i, j, m, n, o) \in S_2$ and the vehicles are relabeled as follows: $l(i) = h^2, l(j) = m^2, l(m) = c^2, l(n) = c^3$, and $l(o) = c^4$.

D. Breakdown

The MAE UAV in the higher-order team shares both the number of targets and their locations with the combat team. In turn, the combat team remains intact and reinitiates the request to form a higher-order team.

The guard conditions associated with rules $r_9$ and $r_{10}$ are true if the combat team clears $m.\text{num}(i, j)$ threats (MAE UAV $i$ is part of the higher-order team and $j \in \mathcal{A}$). In both of these cases, the ISR team is broken, and the HAUE UAV returns to exploring the coordinates in $\mathcal{A}$. The guard conditions associated with rules $r_9$ and $r_{11}$ are true if the combat team dissolves before all threats are cleared. In these two cases, the ISR team remains intact and reinitiates the request to form a higher-order team.

Notice that the breakdown of ISR teams depends on the disbanding of the corresponding higher-order team. This is due to the fact that the formation rules of ISR teams depend on the existence of threats and, once these threats are cleared, the higher-order team is broken along with the ISR team.

E. Advantages

The dolphin-inspired strategy is decentralized and robust, and these characteristics of the strategy were alluded to in Sec. I. More explicitly, in the multilevel coalition formation strategy developed in this paper, vehicles are autonomous, decision-making units (decisions are based on

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Fig. 5 Threats (dot with ring) are searched by HAE UAVs (large plane, square-shaped searching range) that pair with MAE UAVs (small plane, circular searching range) to form ISR teams.
locally available information), and the strategy retains functionality despite the loss of any vehicle in the network. The strategy has certain performance advantages too. These advantages are presented in terms of the search effort.

According to the setup of the SEAD mission discussed in this paper, combat vehicles are incapable of searching for threats. The combat teams approach threats when the location of the threat is passed on to them. The advantage of using ISR teams stems from the fact that MAE UAVs, governed by the bioinspired coordination strategy developed in this work exhaustively search only those coordinates from the set $A$ that potentially pose a threat. This reduces the searching effort considerably for an area that is only sparsely populated with threats.

More formally, consider a network where the number of HAE UAVs and MAE UAVs is $N_H$ and $N_M$, respectively. Moreover, let there be $k$ coordinates in $A$ that contain threat(s); also, let $|A|$ represent the number of coordinates in $A$ (denotes cardinality), and let $\zeta$ coordinates (to be traversed by MAE UAVs) be associated with every coordinate in $A$. According to the dolphin-based coordination strategy, by forming ISR teams, an HAE UAV will search, on average, $|A|/N_H$ coordinates in $A$. In addition, an MAE UAV will search, on average, $k\zeta/N_M$ coordinates. On the other hand, a network that consists of only MAE UAVs as the surveillance vehicles will search, on average, $|A|\zeta/N_M$ coordinates, regardless of the number of threats in the area.

V. Simulations

To demonstrate the viability of the proposed multilevel alliance building algorithm, a simple simulation platform is devised that can capture the key future of this algorithm. The operation of the bioinspired strategy is shown in Figs. 5 and 6. For the ease of presentation, the search area is partitioned into 16 cells, and a dot in the center of a cell represents a coordinate in $A$. A cell is highlighted when explored by at least one HAE UAV. There are four threats (dot with a ring) in the search area, two of which are located in the same cell.

The simulation includes two HAE UAVs (large, planes), three MAE UAVs (small, planes), and five UCAVs (wedges). An exploring HAE UAV is shown with a sensing footprint around it. When an HAE UAV detects a threat (sensing footprint is not shown), it sends a request to form an ISR team. The MAE UAV that accepts this request (shown with a sensing footprint around it) begins searching the cell, and the HAE UAV initiates a holding pattern over that cell. Once the MAE UAV searches the entire cell and confirms a threat, the ISR team sends a request to form a higher-order team. Members of combat teams are indicated by bold lines between them.

A combat team that accepts the request to form a higher-order team locks on to the location of the threat (shown with a dashed line between the combat team and the threat). The mission is complete when every coordinate in $A$ has been explored by at least one HAE UAV. At this point, the vehicles return to their bases (these locations are not shown).

Fig. 6 Five UCAVs (wedge) form two teams: a pair and a triplet. ISR teams from Fig. 5 coordinate with these combat teams to annihilate threats until the area is cleared.
Note that, according to our model, the ISR team prefers to form a higher-order team with the larger UCAV team (Fig. 5e). Moreover, because the capability of combat vehicles decrease after neutralizing threats, notice that the combat pair breaks down in Fig. 6d.

We did not consider potential problems that might arise from potential communication latency in real-life applications. Also, the simulation does not show potential vehicle failures, although the algorithm is capable of handling these cases. The relatively short simulation does not capture the longer endurance of a high-altitude reconnaissance UAV compared to the relatively low endurance of a combat vehicle. However, it validates the performance of key aspects of the algorithm, namely formation of first- and second-order teams of heterogeneous vehicle in a completely decentralized way.

VI. Conclusions

In this work, inspired by the multilevel alliance-forming behavior of bottlenose dolphins, we developed a coordination strategy for a network of autonomous, unmanned vehicles to carry out the suppression of enemy air defenses mission. This mission, envisioned by the U.S. Navy, uses a heterogeneous network that consists of three types of vehicles and requires teams of surveillance vehicles to coordinate with teams of combat vehicles. Based on a mathematical model that expressively captures dolphin alliances, we developed a strategy to effectively build multilevel teams that coordinate with each other to accomplish this search-and-destroy mission through the dissemination of local information in the network. This decentralized algorithm does not rely on an individual agent and is robust to failures. The mathematical framework used here is capable of building more sophisticated teams, should it be necessary. However, we did not address the potential need for radio blackout when unmanned aerial vehicles are within certain range of a threat. Also the possible adversarial effects of potential communication delays on the performance of the algorithm is not addressed here.

Simulations illustrated the operation of the strategy. Among the advantages of the proposed bioinspired strategy, we can note its robustness to loss of vehicles, its scalability to introduction of new vehicles, and reduction of the search effort for areas sparsely populated with threats.

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