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A Behavior-Driven Coordination Control Framework for Target Hunting by UUV Intelligent Swarm

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ABSTRACT One of most primitive problems by unmanned underwater vehicle intelligent swarm (UIS) is coordination control, which has a great significance for realization of target hunting with great performance of efficiency and robustness. Existing studies concentrate on behavior-based centralized or distributed control approaches with the prior knowledge and mostly do not elaborately consider behavior conflicts and constraint differences. Therefore, a novel behavior-driven coordination control framework including topology architecture and swarm control which is inspired by immune mechanism, is investigated for target hunting of heterogeneous UIS under unknown and uncertain environment in this paper. For topology architecture, a hybrid non-central distributed topology is developed as a novel immune-inspired architecture to regulate agents with self-organizational and fault-tolerance features. For swarm control, a dual-layer switching control scheme composed by global control and local control, is proposed to drive behaviors via behavioral-intensity, the trigger of switching is when the target is detected. The global control approach is employed to search target, in which two constraints of energy consumption and healthy-state are considered to achieve good operational reliability. While the local control approach is developed to form the dynamic alliance of tracking and capturing, in which behavioral-intensity control strategy for behavior aggregation and decision-making control strategy for behavior selection are respectively designed to avoid behavior conflicts. Simulation results demonstrate that proposed framework can accomplish hunting under various situations such as hunter agent is random or fixed distribution, and the number of targets asynchronously appears. It is confirmed that our framework is capable of achieving the target hunting under unknown and uncertain environment with greater efficiency and robustness.

INDEX TERMS Target hunting, behavior-driven, coordination control, hybrid non-central topology, dual-layer switching control.

I. INTRODUCTION

Unmanned Underwater Vehicle (UUV) is a submersible underwater vehicle which integrates acoustic detection, information fusion and intelligent control functions while performing a task. However, due to uncertainties, incomplete information and distributed underwater environment, a single UUV cannot perform the complex tasks, such as intelligence surveillance, ocean survey, task allocation, and time-sensitive strike, especially for target hunting in military application [1]–[3]. In contrast, UUV intelligent swarm (UIS) which is composed of amounts of heterogeneous agents, is employed to offset weaknesses of single UUV with more efficiency and robustness [4].

In navy military field, target hunting application for different invaded agents such as torpedo and submarine, is the great significance to study. The comprehensive hunting process contains three continuous and parallel sub-tasks: searching

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potential targets, establishing an dynamic tracking alliance and forming an capturing formation to finally catch target. One primary problem in target hunting is coordination control, in which essence of coordination control is to provide a appropriate hunting alliance for searching, pursuing and capturing target with the possible shortest time and distance. It has been intensively attracted much attention in community of control [2]–[4]. Up to now, numerous methods have been developed to address the problem of target hunting, which can be classified into centralized and distributed two categories.

Centralized category is subject to coordination objective, and generally uses a top-down modeling. Only a few target hunting application have been reported in this category. For example, Bradley and Tshilidzi [5] described centralized hunting architecture with multi-layer perceptron (MLP) neural network, in which the global hunter determines paths of other hunters via genetic algorithm optimization. Although this method is effective, behavior exploration does not avoid in a particular situation where illegal behavior is evaluated due to the fact that one hunter exists more than one direction to move. Cao and Guo [6] developed a leader-follower formation algorithm to assign hunting tasks by multiple autonomous underwater vehicles, and an angle matching strategy was utilized to guide round up target by leading hunter, however its topology is rigid to describe the position of agents, which can cause imperfect robustness, especially for large-scale agents. In the aforementioned works, centralized approaches are capable of achieving target hunting, however drawbacks cannot be ignored in dramatically changing environment.

To overcome drawbacks of centralized approaches, more attention have been attracted on distributed coordination. On the contrary, it adopts a down-top modeling, which essence is that all agents in the swarm have equal status, objective and knowledge, and interact with global or local neighbors via topology architecture and communication protocol to achieve coordination control. More recently, many researchers have proposed a series of remarkable studies on distributed coordination in target hunting applications, all of which can be divided into negotiation method [7]–[9], artificial field method [10], [11], optimization method [13]–[15], neuron-inspired method [16]–[18] and behavior-based method [19]–[28].

Negotiation method is greatly prevalent in target hunting, it imitates economic mechanism of announce-biding-award to achieve coordinate the interactions among the agents. Chen *et al.* [7] proposed a distributed pursuit-evasion algorithm based on interaction protocols of contract net and subscribe-publish, simulations demonstrated that agents can construct several swarm efficiently. Li *et al.* [8] provided a cooperative hunting strategy for multi-mobile robot system, in which negotiation mechanism was applied to allocation the desired hinting point and plan the on-line paths, moreover it has been employed to coordinate in confrontational hunting of two swarms. For example, Zhou *et al.* [9] utilized contract net protocol to design an improving permissively dynamic alliance for multi-agents cooperative hunting. Most of above mentioned algorithms may cause communication decay due to the amounts of interactions among hunters, and the associated hunters will cost more time on re-planning and calculating.

To alleviate the influence of changed environments on target hunting, artificial field method is employed to decide the motion along the gradient of a potential field governed by the target, in which two primary principles of attractive and repulsive forces is always introduced. Escobedo *et al.* [10] proposed artificial field function, in which attractive force between hunters and target, repulsive force among hunters are only introduced to achieve hunting task. Noguchi and Maki [11] described an artificial potential field based on binary Bayes filter to track the sea urchins with an optimized path planning. Xue *et al.* [12] formulated an artificial potential functions for distributed formation with switching typologies and time-varying delays in a multi-agent systems. However, potential field is easy to appear local minimum and deadlock when hunter is subjected to multiple attractive and repulsive forces or the hunter, target and obstacle are geometrically collinear, so adaptability is relatively weak.

Optimization method is utilized to search an optimal position and path according to the targets and the involved constraints. Yang *et al.* [13] formulated a decentralized control hunting scheme of swarm robots for targeting search and trapping inspired by bacteria chemotaxis under the guidance of gradient information, in which a single target is considered. Ishiwaka *et al.* [14] proposed a reinforcement learning algorithm to model how the hunters selecting cooperative behavior to achieve the task, and hunter agents are capable to learn via two kinds of predictions, in which four hunters collaborate to catch a target. In addition, Pan and Li [15] investigated a comparative reinforcement learning algorithm, which based on joint rewards to insure hunter agents to learn behaviors, there is an static target. In these works, optimization method may fail with more than one static or dynamic targets, which existed limitation in real circumstances.

Neuron-inspired method is developed to establish neural-inspired network model with its specific link mechanism for the hunting task. Ni and Yang [16] firstly introduced bio-inspired neural network (BNN) into cooperative hunting to design the dynamic alliance and formation construction. The results exhibited the capability of guiding the agent to achieve the hunting. But, the same neuronal activity in tracking may increase the computing time. Inspired by [16], some others varied BNN algorithms were emerged. For example, Zhu *et al.* [17] designed an BNN-based hunting algorithm of Multi-AUVs, in which a distance-based negotiation approach was put forward to assign the hunting task. To improve the real-time hunting, Chen and Zhu [18] investigated an hunting alliance based on time-competition, and path planning approach integrated BNN model to effectively pursuit the invader. This kind of methods can successfully achieve the hunting, but the searching map is rasterized, and some potential conflicts may not avoid under changing environment.

Behavior-based method is one of significant attention in the field of target hunting, the essence is motivated by natural collective phenomenons. Many biologists, physicists and interdisciplinary scientists have devoted to investigate how swarm exhibits high-level global collective-behavior based on low-level individual distributed intelligence [19], and numerous behavior-based methods have been developed, in which exists two modeling styles. One is the swarm-based macroscopic mode that researches the whole swarm, although it is suitable for larger scale hunter agents, it completely ignores specific individual behavior. The other is individual-based microscopic mode that focus on individual, collective behavior as control parameters to determine the hunting alliance and formation, so this model is the most intuitive and prevalent modeling method in target hunting.

As one landmark work, Couzin *et al.* [20] proposed a distinguished swarm model so-called Vicsek, where agent behaviors abstracted as separation, alignment and cohesion are dominated by the influence of its neighbors. After it was clearly summarized, researchers have put forward a variety of swarm coordination models such as Couzinand [21], social force model [22], asynchronous random model [23] and fuzzy logic model [24]. In the past decade, due to the rapid development of information technology such as image processing, target tracking, massive data analysis and so on, more hidden collective features are excavated, for example Duan *et al.* [25] developed a cooperative decision-making scheme inspired by Grey-wolf swarm for hunting. Most of previous works have concentrated on properties such as congregation, stabilization, cohesion, and quick consensus. However, more prior knowledge is predefined, and strict constraints are needed, moreover behavior conflicts are not avoided, some of which limits the applications.

Inspired by the better performance of immune mechanisms in managing many complex system, Wang *et al.* [26] exploited a coordinated model-inspired by Self/Non-Self defense mechanism, but it is a concept-model without mathematical and experimental verification. Whitbrook *et al.* [27] developed an immune network integrated reinforcing learning for incorporation into behavior-based multi-agent system. This approach formulates an exemplified hybrid artificial immune system to drive the concentration, but some limited behaviors are employed as prior knowledge and target is static without external distribution. Liang *et al.* [28] creatively proposed an immune-agent interactive network (IAIN) for behavior-based formation control of intelligent swarm. This model improves efficiency, but the hunting may fall into due to the conflicts. It is worth noticing that swarm intelligent embedded in immune mechanisms is an important solution for behavior-based coordination of swarm due to the merits of self-organization and flexibility. But the efficiency of this coordination control is limited, and there are few researches of it on target hunting problem of UIS.

In this paper, a behavior-driven coordination control framework based on immune mechanism is creatively proposed to achieve target hunting. In UIS application, it working process involves three phases including searching, tracking and capturing, population is larger, in which hunter agents are heterogeneous, and location of target is unknown and dynamic, and there are more than one targets. In the proposed frame, the topology architecture and swarm control are tightly coupled. The hybrid non-central topology is firstly developed as a novel immune-inspired topology with self-organizational and fault-tolerance features, rather than centralized and fixed formation, which is more suitable to manage target hunting procession. Furthermore, a dual-layer switching control scheme is proposed to drive behavior via a control parameter called behavioral-intensity, in which global control and local control are formulated to optimize behavior selection and avoid behavior conflicts under disturbances and constraints. Simulation results demonstrate that proposed framework can effectively accomplish target hunting with higher efficiency and robustness compared with other existing methods.

The main contributions of this paper are summarized as follows. (1) behavior-driven coordination control framework is firstly proposed to drive and evolve the discrete behaviors for target hunting, and unlike the previous researches, the hunting process is dynamic and unknown like the real world, that is, the target is not static and targets can asynchronously appear. (2) The proposed control framework is inspired and integrated by immune mechanisms such as immune network, clonal selection and danger model to establish a dynamic hunting alliance, which is extended bio-inspired application ranges. (3) The two constraints such as energy consumption and healthy state are considered to filter out inferior hunter agents in order to improve the operational reliability. (4) The behavior conflicts are solved by using behavioral-intensity control strategy for behavior aggregation and decision-making control strategy for behavior selection. (5) In the proposed framework, hunting time, energy consumption and hunting distance are better than comparative approaches in the same scenario, all the results proves the great adaptability, robustness and efficiency of our framework.

The remainder of this paper is organized as follows. Section II describes preliminary knowledge and problem statement. Section III presents behavior-driven coordination control framework. Section IV designs the hybrid non-central distributed topology. Section V details dual-layer switching control scheme. Section VI performs extensive experiments to prove the efficiency and robustness. Finally, conclusion and future work is provided in Section VII.

II. PRELIMINARY KNOWLEDGE AND PROBLEM STATEMENT

A. TARGET HUNTING OF UIS

UIS is becoming an indispensable unmanned undersea combat future-style, which is composed of large-scale heterogeneous agents. Compared with the traditional multi-UUV cooperative system, it exists four outstanding features such as space distribution, time distribution, resource distribution

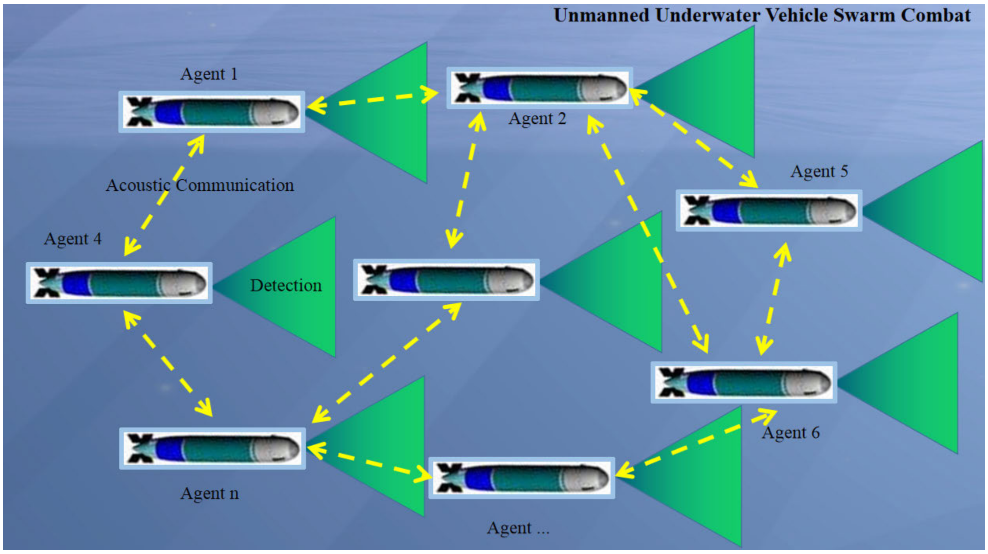

FIGURE 1. Conceptual schematic of UIS.

and information distribution. It is more desirable for an intelligence swarm that is similar with flocks of birds, schools of fishes and colonies of bacteria and so on. The target hunting is one of significant applications of UIS, in which hunter agent has an integrated capability of searching, tracking and capturing in order to eliminate different-shape intruders and achieve an optimal operational effectiveness due to its high robustness, intelligence, and coordination. Fig.1 demonstrates the conceptual schematic of UIS, each hunter agent has its specific communicating and detecting range, the triangle denotes the detecting fan, and the dotted line denotes the distance of acoustic communication, and the dashed arrows denotes the communication direction. All hunters are deployed in a combat environment and interacts with its neighbors to search, track and capture the potential targets.

However, underwater target hunting is different from the ground and aerial hunting due to dynamic and unstructured environment, such as external disturbance, acoustic delay and data loss and so on, all of which may impact on the healthy states and cause failures in task allocation. Moreover, UUV in a hunting alliance is heterogeneous, each individual agent possess distinct ability, such as communicating range, detecting range and energy consumption, all of which also affect on efficiency and robustness of swarm control. In addition, target hunting in practice is different from foraging problem in multi-robots, the target has a certain of intelligent to escape, thus target hunting is particularly challenging in UIS. The above hybrid reason is a motivation to propose the behavior-driven coordination control framework in this paper.

B. PROBLEM STATEMENT

In this paper, target hunting problem of UIS is described as follows. Consider a multi-UUVs composed with a group of hunter agents and enemy targets navigating in a 2D boundless underwater environment. In this scenario, all hunters and targets deploys the manner of passive detection due to underwater concealment, and each hunter agent has knowledge about neither the environment nor the locations, and each target is asynchronous to be deployed in combat environment. We mainly investigate the searching, perusing and capturing process of target hunting, hunter agent moves towards target, while target changes its direction to escape.

In searching stage, all hunter agents navigate in unknown environment and detect targets. Once a hunter agent firstly detects an invaded target in its detection range, who become the role of information center to bridge a cooperative hunting of this target. In tracking stage, the hunter associated with role of information center is selflessly broadcasting to other neighbor hunter agents in its communication range, then all hunters track towards the target, a local hunting alliance is established. In capturing stage, a number of agents in the established hunting alliance is determined by threaten factor of different-shape target, if threaten factor associated with target such as submarine, is bigger, large number of agents are needed for aggregation. Otherwise, smaller number of agents are considered for smaller threaten factor associated with the target such as torpedo. Once the number of hunter agents is satisfied to threshold of operational effectiveness, which is implied that the target is successfully capturing. The flow of target hunting is shown in Fig.2.

As shown in Fig.2, several discrete behaviors implied in target hunting task are executed to perform stages of searching, tracking and capturing in unknown environment, how to organize, manage and optimize these behaviors is a fundamental problem, since it determines the topology and control. Moreover, to complete the efficiency and robustness of target hunting, some associated issues in swarm control need to be addressed, such as uncertain constraints and behavior conflicts. The above mentioned problems in target hunting will

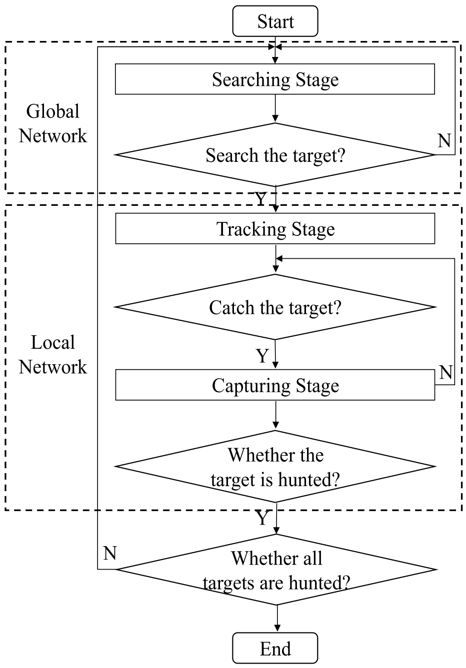

FIGURE 2. **Hunting task flow chart.**

be solved by using the proposed behavior-driven coordination control framework.

1) ASSUMPTION FOR HUNTER AGENT

In this subsection, some assumptions for hunter agent are listed as follows, which are necessary in describing process of searching, tracking and capturing.

Assumption 1: The UIS initially forms a global searching network $\boldsymbol{N_G}$, if anyone target $\boldsymbol{T}$ is detected by any UUV, balance of global network is smashed, then $\boldsymbol{N_G}$ is divided into several subgroups as local tracking network $\boldsymbol{N_L}$.

Assumption 2: The UIS is a heterogeneous swarm, each UUV is able to move omnidirectionally with its ability of detecting range $\boldsymbol{D_R}$, and communicating range $\boldsymbol{C_R}$.

Assumption 3: The UUV moves in horizontal plane at a constant depth, and its kinematic and dynamic are formulated in two coordinate frame [29], body-fixed frame $\{E\}$ and earth-fixed frame$\{B\}$, as illustrated in Fig.3.

In body-fixed frame, kinematic and dynamic with standard nomenclature can be described as

$$\boldsymbol{M}\dot{\boldsymbol{v}} + \boldsymbol{C}(\boldsymbol{v})\boldsymbol{v} + \boldsymbol{D}(\boldsymbol{v})\boldsymbol{v} + \boldsymbol{g}(\boldsymbol{\eta}) = \boldsymbol{\tau} + \boldsymbol{w} \tag{1}$$

where $\boldsymbol{\eta} = [x, y, \psi]^T$ denotes the position and heading angle in earth-fixed frame, and $\boldsymbol{v} = [u, v, r]^T$ denotes velocity in body-fixed frame, where u is a linear velocity in the surge, v is a linear velocity in sway, and r is a angular velocity in yaw. $\boldsymbol{\tau} = [\tau_u, \tau_v, \tau_r]^T$ denotes control input forces, and $\boldsymbol{w} = \left[w_x, w_y, w_\psi\right]^T$ denotes external disturbance. Without loss of generality, $\boldsymbol{g}(\boldsymbol{\eta})$ is a vector of buoyancy and gravitational forces and moments to set as $\boldsymbol{g}(\boldsymbol{\eta}) = 0$, and $\boldsymbol{M}$, $\boldsymbol{C}(\boldsymbol{v})$ and $\boldsymbol{D}(\boldsymbol{v})$ are inertia matrix, centripetal and Coriolis matrix, and

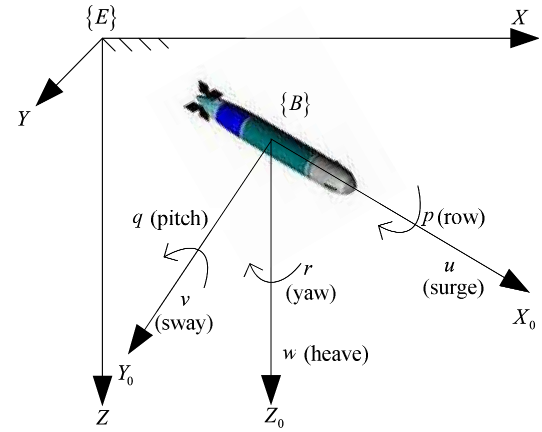

FIGURE 3. **UUV model in horizontal plane.**

hydrodynamic damping matrix, respectively, which are given as

$$\boldsymbol{M} = \begin{bmatrix} m_{11} & 0 & 0 \\ 0 & m_{22} & 0 \;\; v \\ 0 & 0 & m_{33} \end{bmatrix}, \quad \boldsymbol{D}(\boldsymbol{v}) = \begin{bmatrix} d_{11} & 0 & 0 \\ 0 & d_{22} & 0 \\ 0 & 0 & d_{33} \end{bmatrix} \tag{2}$$

$$\boldsymbol{C}(\boldsymbol{v}) = \begin{bmatrix} 0 & 0 & -m_{22}v \\ 0 & 0 & m_{11}u \\ m_{22}v & -m_{11}u & 0 \end{bmatrix} \tag{3}$$

where $m_{11} = m - X_{\dot{u}}$, $m_{22} = m - Y_{\dot{v}}$, $m_{33} = I_z - N_{\dot{r}}$, $d_{11} = X_u + X_{u|u}|u|$, $d_{22} = Y_v + Y_{v|v}|v|$ and $d_{22} = N_r + N_{r|r}|r|$. Moreover, UUV position in earth-fixed frame is described

$$\dot{\boldsymbol{\eta}} = \boldsymbol{J}(\psi)\boldsymbol{v} \tag{4}$$

$$\boldsymbol{J}(\psi) = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{5}$$

where $\boldsymbol{J}(\psi)$ is the transformation matrix.

Assumption 4: For time-varying disturbances, existing three constants $\bar{w}_x \in \mathbf{R}^+$, $\bar{w}_y \in \mathbf{R}^+$ and $\bar{w}_\psi \in \mathbf{R}^+$, $\forall t > t_0$ such that $\|w_x\| \leq \bar{w}_x$, $\|w_y\| \leq \bar{w}_y$ and $\|w_\psi\| \leq \bar{w}_\psi$ [30].

Assumption 5: The UUV is simplified as a mass-point for studying coordinated control of behavioral interaction to be more convenient. The simplified point-mass model based on Eq.(1)~(5) is used for each UUV [48].

$$\boldsymbol{M}\frac{\mathrm{d}\boldsymbol{v}}{\mathrm{d}t} = \boldsymbol{\tau} + \boldsymbol{w}, \quad \dot{\boldsymbol{\eta}} = \boldsymbol{J}(\psi)\boldsymbol{v} \tag{6}$$

Assumption 6: The UUV is subject to the constraints of healthy states and energy, and the energy consumption rate of UUV is different among all the behaviors. Those two constraints can affect the behavior selection and execution.

Assumption 7: The behavior for each UUV in hunting process is composed of five discrete events as illustrated in Table 1. One behavior $b^l \in [\boldsymbol{B_S}, \boldsymbol{B_N}, \boldsymbol{B_D}, \boldsymbol{B_C}, \boldsymbol{B_M}]$ is given a priority structure $\boldsymbol{P}^l$ based on the principle that the need of some situations outweigh those of others, $l = 1,2, \ldots, \boldsymbol{Q}$, $\boldsymbol{Q}$=5, and the label of l is consistent with the value of priority, that is, $\boldsymbol{B_S}$ is set with the lowest priority $\boldsymbol{P}^l = 1$, $\boldsymbol{B_M}$ is the

TABLE 1. Discrete behavior and its priority.

Behavior	Notation (b^l)	Description	Priority(P^l)
Stopping	B_S (l=1)	UUV can not become a member of global network N_G and local network N_L due to the constraints of healthy states and energy	1-Lowest
Navigating	B_N (l=2)	UIS initially navigate in unknown and uncertain environment to establish global tracking network N_G	2
Detecting	B_D (l=3)	If an UUV firstly detects the target T , it automatically become the information center in the unformed local network N_L	3
Communicating	B_C (l=4)	The information center broadcasts the invasive information to its neighbors in local the track and capture network N_L	4
Moving	B_M (l=5)	Notified UUVs move and follow with the agent that detected the enemy target T to perform hunting alliance	5-Highest

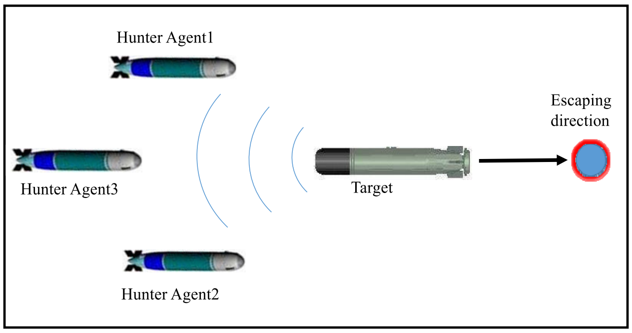

FIGURE 4. **The first escaping strategy when tracking alliance has two hunter agent.**

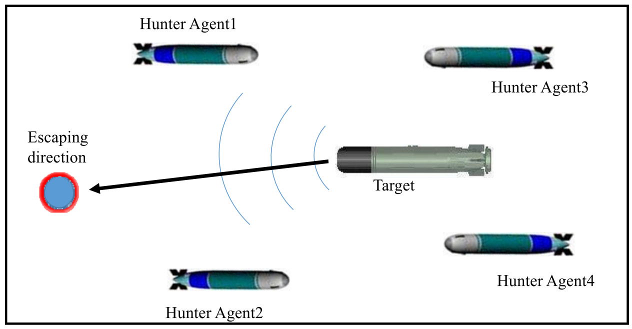

FIGURE 5. **The second escaping strategy when tracking alliance has more than two hunter agent.**

highest priority $\boldsymbol{P}^l = 5$, and $\boldsymbol{B_N}$, $\boldsymbol{B_D}$ and $\boldsymbol{B_C}$ are sorted by priority from low to high, all of which can enable hunting alliance of $\boldsymbol{N_L}$ is established.

2) ASSUMPTION FOR TARGET

In this subsection, assumptions for target are listed as follows, which are necessary in describing process of navigating and escaping.

Assumption 1: The target $\boldsymbol{T}$ in hunting tasks exists two categories such as large-shape and small-shape, difference is the value of detecting range $\boldsymbol{T_R}$ and threaten factor $\boldsymbol{\vartheta}$.

Assumption 2: The kinematic and dynamic model of each target $\boldsymbol{T}$ is similar to hunter agent, but for simplicity, only dynamic is taken into consideration, as demonstrated

$$\dot{\boldsymbol{\eta}}_{\boldsymbol{T}} = \boldsymbol{J}(\boldsymbol{\psi}_T)v_T \tag{7}$$

where $\boldsymbol{\eta_T} = [x_T, y_T, \psi_T]$ denotes position vector, (x_T, y_T) is the position coordinates, ψ_T is the heading, $\boldsymbol{v}_T$ is velocity, and $\boldsymbol{J}(\psi_T)$ is a transformation matrix that is the same with Eq.(5).

Assumption 3: The target $\boldsymbol{T}$ moves straightforward initially. If it detects hunter agent in its $\boldsymbol{T_R}$, and hunter agents are more than two, then the target $\boldsymbol{T}$ automatically selects a one from two escaping strategies to be implemented [18], which are demonstrated as Fig.4 and Fig.5, respectively. The Fig.4 describes the first strategy that target $\boldsymbol{T}$ turns its direction against two hunter agents (hunter agent 1 and hunter agent 2) in its $\boldsymbol{T_R}$, and Fig.5 describes the second strategy that the target $\boldsymbol{T}$ turns its direction to the midpoint of two involved hunter agent in the tracking alliance with a largest distance $\boldsymbol{L}_{ij} = \max\{\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}\}$, where i, j is a label for hunter agent i and hunter agent j, respectively. For example, the target escapes between hunter agent1 and agent2.

Assumption 4: The target $\boldsymbol{T}$ keeps healthy state, and move omnidirectionally to reversely detect hunter agents.

Assumption 5: The target $\boldsymbol{T}$ is not subject to time delays in turning navigating directions, and the turning radius is ignorable.

Assumption 6: The target $\boldsymbol{T}$ is dynamic, and a confrontation derived from target swarm is ignored.

III. BEHAVIOR-DRIVEN COORDINATION CONTROL FRAMEWORK

In this section, we propose a behavior-driven coordination control framework inspired by immune mechanism for target hunting. Thus, the involved immune mechanism and control framework are briefly demonstrated.

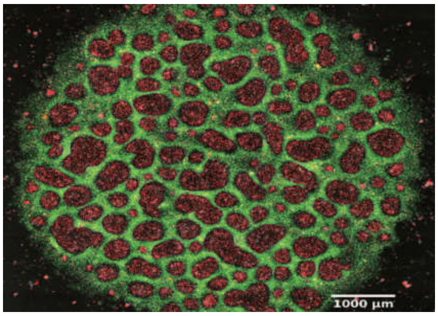

FIGURE 6. An example of immune system under the microscope [31].

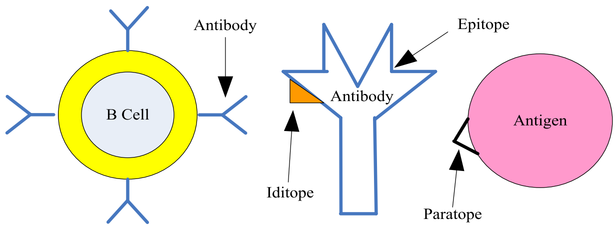

FIGURE 7. B-cell and antibody and antigen.

A. IMMUNE MECHANISM

Vertebrate immune system (IS), involving a large amounts of cells and molecules as shown in Fig.6, protects its host from dangerous invading agents, known as antigens. Immune responses to invading antigens are triggered by perceiving and eliminating of antibody, in which the process is an elaborate and dynamic multiple-layer defensive mechanism, namely innate immune and adaptive immune [31], [32]. Innate immune is an inherent immunity in non-antigen specific manner, which fulfills initial regulating immune response for antigens. Whereas, adaptive immune plays a key role in robust respond against invaded antigens that innate immune system cannot eliminate with an antigen specific manner.

In adaptive immune, basic components are lymphocytes that are classified into as two major types, B lymphocyte (B-Cell) and lymphocyte T (T-Cell), which can affect different immune functions, B-Cell chiefly works by secreting substance called antibody in blood to recognize and eliminate invading microorganism called antigen, and T-Cell regulates and mediate the secreted antibody from B-Cell.

B-Cells are maturing in bone marrow, all of which have distinct structure and secretes“Y”shaped antibodies from its surfaces. The antibody recognizes and binds specific antigen by a receptor called paratope, and the corresponding binding region of antigen is antigen determinant called epitope as illustrated in Fig.7. Paratope and epitope are complimentary and analogous to key and keyhole. Moreover, antibody is relatively specific to the antigen, and specificity degree is determined by the affinity of couple antigen-antibody.

Over the decades, immunologists have developed a series of immune mechanisms to fulfill interpretation the adaptive immune. For example, clonal selection, immune network and danger model, which are briefly reviewed.

Clonal selection theory emphasizes that paratope of B-cells have a high affinity to an epitope derived from the stimulated antigen is selected to proliferate and differentiate the plasma cells and memory cells. Once antibody paratope binds to entigen epitopes, it driven others cells to assist with elimination. In this matching process, some of the matching B-cell are retained as memory cells to quickly improve the concentrations of the specific B-cell when the same antigen invades again. Inspired by this theory, the famous clonal-selection algorithm and negative selection algorithm and their variations have been developed to tackle path planning, and optimization associated with swarm intelligent [34], [35].

Immune network theory is proposed to explain working of IS in absence of invading antigens or suppression of certain immune function that clonal selection theory is not illustrated. It is suggested that antibodies are not only stimulated by antigen, but also exists the stimulation and suppression between antibodies. The computational model of idiotypic network was proposed by Farmer and Packard [32], which is derived from changing of antibody concentration via the suppression, stimulation and natural death rates. This theory is the most popular immune model for incorporation into coordination control because it involves interantibody stimulation and suppression, as well as matching to antigens. Its main challenge is the definition of antigen, antibody and their dynamic in real circumstances [34].

Danger model theory, as a newer definitions of Self-Nonself discrimination model, was proposed by Matzinger [36] to extend clonal selections of antibody production of activated B-cells. It suggests that IS is more concerned with damage than foreignness, rather than by the recognition of non-self. In this theory, B-cells recognize and internalize the injured/stressed agents, and these agents undergoes different processes, in which due to insufficient activation of T-helper cells on recognition signal 1, a specific co-stimulation signal 2 from dendritic cell (DC), also termed as antigen presenting cell (APC), is needed to completely activate the T-cells, as shown in Fig.8. Once activated, all DCs provide co-stimulation to demonstrate the innate or adaptive immune response. Moreover, DCs contains immature DC, semi-mature DC and mature DC, in which immature DCs collect injured/stressed agents, and further activate in terms of safe signal or danger signal from its neighboring environment. If environment is safe, DC becomes semi-mature and presents antigen to T-cell that causes the T-cell-tolerance. By contrast, if environment is dangerous, DC becomes mature to completely activate T-cell that produce antibodies to eliminate the antigen.

Compared with the clonal selection and immune network, danger theory is a new definition of immune system, its dentritic cell algorithm and toll-like-receptor algorithm [37] all mimic underlying translations of the involved signal models and roles. For example, a DC-inspired subsumption architecture is implemented to coordinate among various behaviors in avoid obstacle, but this is a classification issue that can not fully incorporate the behavior necessary for navigation [38].

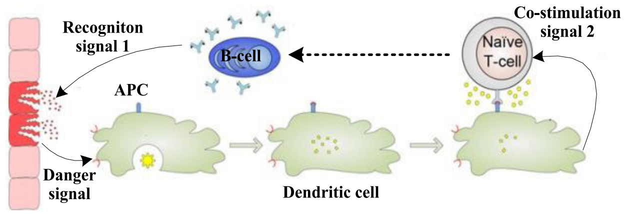

FIGURE 8. Immune mechanism of danger theory.

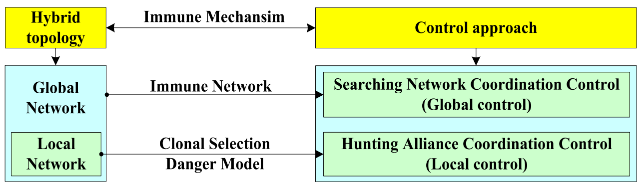

FIGURE 9. Behavior-driven coordination control.

Overall, IS which is essentially a swarm intelligent system, involves rich metaphorical immune-mechanisms. Due to the great self-organization, robustness and adaptation and so on, these mechanisms can be employed to coordinate and control applications. Therefore, we can adopt some useful metaphors to develop an appropriate framework for target hunting, which is the other motivation in this paper.

B. DISTRIBUTED COORDINATION CONTROL FRAMEWORK

The behavior-driven control framework is formulated to address the coordination control for target hunting as shown in Fig.9, which is composed of hybrid topology and control approach.

The hybrid non-central distributed topology inspired by the immune mechanisms is creatively proposed as a novel distributed topology to regulate agents involved into local network and global network. And an dual-layer switching control scheme is developed to perform collective behavior for target hunting, in which there exists two control approaches, namely global control and local control. One is the global searching network coordination control inspired by immune network, which corresponds to the searching stage. The other is the hunting alliance coordination control approach inspired by clonal selection and danger model, which corresponds to the tracking and capturing stage. Furthermore, two constraints of energy consumption and healthy state are modelled in global control to achieve operational reliability, and behavioral-intensity control strategy for behavior aggregation and decision-making control strategy for behavior selection are designed to avoid behavior conflicts. Noting that behavioral-density is the only one control parameter of dual-layer switching scheme, and the trigger of switching is when the invaded target is detected.

C. MAPPING RELATIONSHIP OF STRUCTURAL AND FUNCTIONAL CONSISTENCY

In order to clearly exhibits work of the proposed control framework, the analogous mapping relationship of IS and UIS is given from the viewpoint of structural and functional consistency. As discussed in section II-A and section III-A, it has an obviously remarkable similarity from architecture and function, two systems are all distributed architecture and defense mechanism. Therefore, an elaborate mapping can be established as shown in Table 2, which is useful to study intrinsic mechanism of our proposed framework in this paper.

TABLE 2. Analogous mapping relationship between UIS and IS.

UIS	IS
Target Hunting	Defense mechanism
Hunter agent(UUV)	B-cell
Enemy target (invader)	Antigen
Behavior module	Antibody
Behavioral-intensity	Antibody concentration
Detecting target	Antigen stimulated
Behavioral-intensity reinforce	Antibody stimulated
Behavioral-intensity weaken	Antibody suppressed
Capturing target	Elimination antigen

Definition 1. Defense mechanism of IS is defined as target hunting of UIS, thus the associated immune-mechanisms can be designed to describe the searching, tracking and capturing processes of hunting task.

Definition 2. B-cell is defined as a hunter agent $\boldsymbol{U}_i \in [\boldsymbol{U}_1, \boldsymbol{U}_2, \cdots, \boldsymbol{U}_N]$, $i = 1,2,\ldots, \boldsymbol{N}$, and $\boldsymbol{N}$ is the number of hunter agents. Its dynamic model is denoted as Eq.(5), and each $\boldsymbol{U}_i$ is subjected to all Assumptions 1∼7.

Definition 3. Antigen is defined as a invaded target $\boldsymbol{T}_j \in [\boldsymbol{T}_1, \boldsymbol{T}_2, \cdots, \boldsymbol{T}_W]$ that invades into uncertain environment, $j = 1,2,\ldots, \boldsymbol{W}$, and $\boldsymbol{W}$ is the number of targets. Its dynamic model is denoted as Eq.(7), and $\boldsymbol{T}_j$ is subjected to all Assumptions 1∼6.

Definition 4. Antibody is defined as a behavior module $b^l \in [\boldsymbol{B_S}, \boldsymbol{B_N}, \boldsymbol{B_D}, \boldsymbol{B_C}, \boldsymbol{B_M}]$, $l = 1,2,\ldots,\boldsymbol{Q}$, and $\boldsymbol{Q}$=5 is the number of behavior types listed in Table1. The selection of an appropriate behavior onboard agent $\boldsymbol{U_i}$ is determined by local interactions with target and its neighbors $\boldsymbol{U}_j, j = 1,2,\ldots \boldsymbol{N}_i, \boldsymbol{N}_i = \{j|\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \leq \boldsymbol{C_R}\}$.

Definition 5. Antibody concentration is defined as behavioral-intensity. The behavioral-intensity Ω is an unique global control parameter to coordinate hunter collective behaviors.

Definition 6. Antigen stimulated is defined as Detecting target. If a target $\boldsymbol{T}_j$ is detected by any agent, global network $\boldsymbol{N_G}$ is stimulated and the balance is broken, which is driven the forming of local network $\boldsymbol{N}_L$. Furthermore, the number of Antigen stimulated decides the number of $\boldsymbol{N}_L$.

Definition 7. Antibody stimulated is defined as Behavioral-intensity reinforce. It implies that more behaviors are needed to rapidly gain intensity level from neighbour $\boldsymbol{U}_j$ in $\boldsymbol{C_R}$, then an efficient $\boldsymbol{N}_L$ can be successfully established to accomplish hunting task for the target $\boldsymbol{T}_j$.

Definition 8. Antibody suppressed is defined as Behavioral-intensity weaken. It implies that the behaviors are

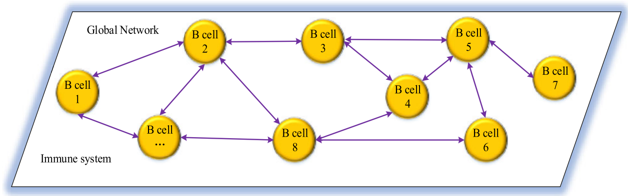

FIGURE 10. Schematic diagram of global network without antigenic stimulation.

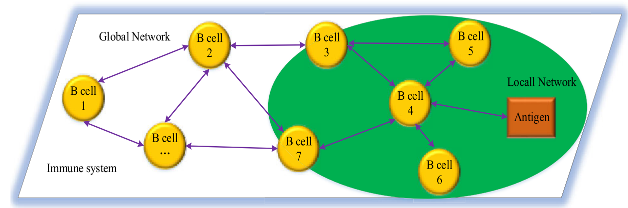

FIGURE 11. Schematic diagram of local network with an antigenic stimulation.

needed to rapidly decline to a certain intensity level, then an effective N_L can be elaborately established in order to avoid behavior conflicts.

Definition 9. Elimination antigen is defined as Capturing target. If a certain number of agents stimulated and suppressed are allocated to hunt target T_j, and this T_j can be modeled as capturing in N_L.

IV. HYBRID NON-CENTRAL DISTRIBUTED TOPOLOGY

In a multi-agents, a topology is of significance to swarm control, which determines how agent communication with each other, what are the control capabilities of each agent, and how efficient of coordination [39]. That is an appropriate topology plays a critical role to address coordination and cooperation. Generally, there are three prevalent topologies, which are star-like, web-like and hierarchy-like, respectively [40]. (1) Star-like topology is suitable for applications of centralized behavior-control, but it exists a communication bottleneck due to the critical point of failure. (2) web-like topology can establish a complete graph with a uniform interaction, so flexibility is the benefit in this topology, but indiscriminative interaction is often inefficient. And (3) hierarchy-like topology involve agents, all of which are grouped in multi-layers, and all layers are organized in hierarchy. It has trade-off ability between centralized and distributed control due to hierarchical function design of behavior interactions. Although previous three types facilitates topological models, all of which can not well solve dynamic evolution and asynchronous reconstruction required in unknown and uncertain environment. It is the reason why three types are imperfect to govern behavior interaction in target hunting. Therefore, a hybrid non-central distributed topology inspired by the immune-response is proposed for proposed control framework.

In immune hypothesis [31]–[38], each B-cell within immune system interacts with a group of B-cells in its neighborhood by stimulus1 from external antigen with paratope-epitope connection, stimulus2 from other antibodies with idiotope-paratope connection and suppression from other antibodies with paratope-idiotope connection. In addition, those interactions can exist even in absence of antigen, as exhibited in Fig.10∼11. Fig.10 describes a global network without antigenic stimulation, whereas Fig.11 describes a local network when an antigen breaks stability of global network. By analogy, if there are several invading antigens, multiple local networks are formed in global network.

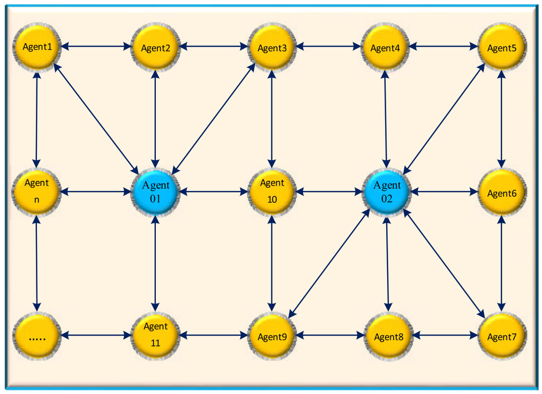

FIGURE 12. Schematic diagram of hybrid non-central distributed topology.

Inspired by this immune mechanism, if a B-cell is termed as an agent, global network and local network naturally are formed an multi-agent system (MAS). Furthermore, from the topology architecture viewpoint of graph theory, a hybrid non-central distributed topology is proposed in Fig.12.

As shown in Fig.12, there are two local networks in global network, one is composed of Agent1, Agent2, Agent3, Agent10, Agent11, Agent n and Agent01, where Agent 01 is considered as virtual local coordinator, and the other is composed of Agent4, Agent5, Agent6, Agent7, Agent8, Agent9 and Agent02, where Agent02 is also considered as virtual local coordinator. The virtual local coordinator is similar the central supervisor in star-like topology but is not same with it, because it only plays a bridge-transferring role of interactive information, which implies that no any control function takes place there, hence the agent is called as virtual local coordinator.

Clearly, our proposed topology is more sophisticated, and which completely absorbs all outstanding features from the previous web-like, star-like and hierarchy-like topology. It characterize great self-organization and fault-tolerance. Compared with previous topology, some properties implied can be summarized in Table3.

V. DUAL-LAYER SWITCHING CONTROL SCHEME

This section elaborately demonstrates the proposed dual-layer switching control scheme in framework, this scheme coupled with hybrid non-central distributed topology is composed of global control and local control that corresponds

TABLE 3. Properties of four MAS topology.

Properties	Star-like	Web-like	Hierarchy-like	Proposed
Center controller	YES	NO	NO	NO
Complete communication	NO	YES	Partly	Partly
Dynamic evolution	NO	Partly	Partly	YES
Fault-tolerance	NO	Partly	Partly	YES
Automatic response	NO	Partly	Partly	YES

with global network and local network, where global control is designed to control the searching stage of target hunting, while local control is designed to control tracking and capturing of hunting alliance in local network. Therefore, employing analogous mapping relationship in Table 2, the behavioral-intensity is given by calculating behavior-interactions and driven to perform target hunting.

A. GLOBAL CONTROL FOR SEARCHING

In the initial stage, all hunter agents are distributed to search the potential targets, and behavior $\boldsymbol{B_N}$ is employed to each agent. The behavioral-intensity is determined by local neighbour agents and external disturbance. Moreover, energy consumption and healthy state for each involved hunter agent are two important constraints that achieve the better operational reliability. Therefore, the most basic driven-model under constraints is developed to search target in global control.

1) GLOBAL CONTROL APPROACH

The global control approach is derived from immune-network mechanism, in which all agents dynamically forms an interactively global searching network $\boldsymbol{N_L}$, which is consistent with the schematic diagram in Fig.10. Thus, the behavior-driven global control approach is developed via behavioral-intensity:

$$\dot{\Omega}(b_i^l(t)) = \boldsymbol{\kappa_1}[\Omega_1(t) + \Omega_2(t)] - \boldsymbol{\kappa}_2\Omega_3(t) \tag{8}$$

where $\Omega(b_i^l(t))$ denotes the behavioral-intensity of l-th behavior onboard i-th hunt agent at t-th time, $l = 1,2,\ldots,\boldsymbol{Q}$, $i = 1,2,\ldots, \boldsymbol{N}$, and $\boldsymbol{N}$ is the number of hunter agents. And $\boldsymbol{\kappa_1}$ and $\boldsymbol{\kappa}_2$ denote a positive constant and death factor, respectively. It consists of three parts, Ω_1, Ω_2 and Ω_3.

Ω_1 denotes the behavioral-intensity that is derived from stimulated and suppressed interactions among hunter agents to perform optimal coverage, which is an integrated term of stimulus and suppression, and defines as

$$\Omega_1(t) = \sum_{h=1}^{\boldsymbol{Q}-1}\sum_{j=1}^{\boldsymbol{N}_i}(\Theta_{lh} - \Theta_{hl})b_j^h(t)b_i^l(t) \tag{9}$$

where $h = 1, 2, \ldots Q - 1$ denotes other behaviors excluding l-th behavior, $\boldsymbol{N}_i$ denotes community of agent in communication range of i-th agent, $j = 1,2,\ldots,\boldsymbol{N}_i$. The Θ_{lh} and Θ_{hl} are matching functions between h-th behavior and l-th behavior belonging to any two agents.

Ω_2 denotes the behavioral-intensity that is an additional parameter derived from external disturbance model. Due to external dynamic and unstructured underwater environment, there exists a variety of disturbance and constrains from current field, acoustic field and light field, and those disturbance and constrains are time-varying, resulting in the delay and loss of behavior information, and even affect the interacting and coordination among all agents. Due to the great performance of incremental-independence, time-independence and self-radiation in error modeling [47], so randomization weierstrass function derived from Fractional Brownian Motion (FBM) is employed as the environment stimulation function

$$\Omega_2(t) = a_1 g - \Delta \sin(gt + d_1) + \sum_{n=2} a_n g^{-n\Delta} \sin(g^n t + d_n) \tag{10}$$

where g is a positive constant, $g > 1$, $a_n \in N(0, 1)$ is subject to standardized normal-distribution, $d_n \in [0, 2\pi]$ is subject to the uniform-distribution, $\Delta \in [0, 1]$ is a roughness index that ensure the rationality of random error, and t is the time.

Ω_3 denotes the behavioral-intensity that is derived from natural disappear due to absence of behavioral interaction. As analyzed in section V-B, each agent in hunting swarm has its specific healthy state and energy consumption, if a healthy state can not facilitate to accomplish the behavior or energy consumption exceeds its maximum threshold, this associated agent can't participate in global network via any manner. So Ω_3 is defined as

$$\Omega_3(t) = \mu b_i^l(t) b_i^l(t) = \frac{1}{\sigma + \exp(0.5 - \Omega(b_i^l(t))} \tag{11}$$

where σ is a positive constant.

Furthermore, behavioral-intensity Ω in driven model of Eq.(8) can be rewritten by k iteration number

$$\Omega(k) = \Omega(k-1) + \kappa_1[\Omega_1(k-1) + \Omega_2(k-1)] - kappa_2\Omega_3(k-1) \tag{12}$$

In Eq.(8) and Eq.(12), behavioral-intensity constructs the global searching control approach that facilitates agents associated behaviors to drive the distributed network. Specifically, each hunter agent can execute the real-time evaluation all of its behaviors via behavioral-intensity, in which the elaborate b_{op} is selected to detect any targets.

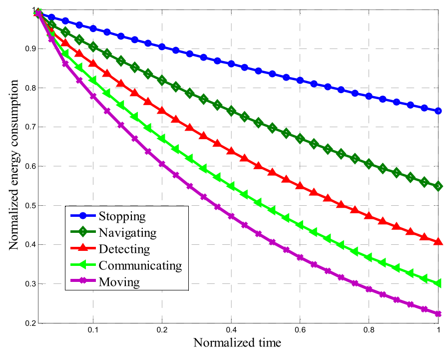

FIGURE 13. Normalized energy consumption rate of different behaviors.

2) ENERGY CONSUMPTION AND HEALTHY STATE

Each individual hunter agent $\boldsymbol{U}_i$ costs energy and faces uncertain healthy state in coordination control due to the behaviour b^l, if the total energy consumption exceeds maximum threshold $\mathbf{E}_{\max}$ or total state-value lower than minimum threshold $\mathbf{H}_{\min}$, this agent can not be allocated any hunter task. It ensures that the faulty agents are removed for the control to be more adaptive and robust.

(1) For energy constraint, $\boldsymbol{U}_i$ executes behavior b^l chosen from $\{\boldsymbol{B_S}, \boldsymbol{B_N}, \boldsymbol{B_D}, \boldsymbol{B_C}, \boldsymbol{B_M}\}$, and the energy consumption rate $\boldsymbol{f_E}(b_i^l)$ of each behavior is different. For example, $\boldsymbol{B_M}$ is the biggest, the reason is that hunter agent supported by the stronger power quickly track target, and $\boldsymbol{B_S}$ is the smallest due to the insufficient energy or poor healthy states. Moreover, the $\boldsymbol{f_E}(b_i^l)$ for $\boldsymbol{B_N}$, $\boldsymbol{B_D}$ and $\boldsymbol{B_C}$ is sequentially inserted between $\boldsymbol{B_S}$ and $\boldsymbol{B_M}$, all of which is modeled on experimental real-data from practical mission. The $\boldsymbol{f_E}(b_i^l)$ is denoted as

$$\boldsymbol{f_E}(b_i^l) = \begin{cases} \exp(-0.01 \times k) & b^l \leftarrow \boldsymbol{B_S} \\ \exp(-0.02 \times k) & b^l \leftarrow \boldsymbol{B_N} \\ \exp(-0.03 \times k) & b^l \leftarrow \boldsymbol{B_D} \\ \exp(-0.04 \times k) & b^l \leftarrow \boldsymbol{B_C} \\ \exp(-0.05 \times k) & b^l \leftarrow \boldsymbol{B_M} \end{cases} \tag{13}$$

where $i = 1{,}2....\boldsymbol{N}$, $l = 1{,}2,...\boldsymbol{Q}$, k is the number of iteration. And normalized energy consumption rates is plotted in Fig.13.

Thus, total energy consumption $\mathbf{E}_T(U_i^k)$ is accumulated over iteration k:

$$\mathbf{E}_T(U_i^k) = \sum_{i=1}^{k_1} f_E(b_i^1) + \sum_{i=1}^{k_2} f_E(b_i^2) + \sum_{i=1}^{k_3} f_E(b_i^3) + \sum_{i=1}^{k_4} f_E(b_i^4) + \sum_{i=1}^{k_5} f_E(b_i^5) \tag{14}$$

where, $k = k_1 + k_2 + k_3 + k_4 + k_5$.

If $\mathbf{E}_T(U_i^k)$ exceeds the maximum threshold $\mathbf{E}_{\max}$, the $\boldsymbol{U}_i$ automatically selects the behavior of $b_i^l = \boldsymbol{B_S}$, which is implied the death. Otherwise, the hunter can selects any behavior, it is given

$$\begin{cases} b_i^l \leftarrow \boldsymbol{B_S}, & \mathbf{E}_T(\boldsymbol{U}_i^k) \geq \mathbf{E}_{\max} \\ b_i^l \leftarrow \{\boldsymbol{B_N}, \boldsymbol{B_D}, \boldsymbol{B_C}, \boldsymbol{B_M}\}, & b\mathbf{E}_T(\boldsymbol{U}_i^k) < \mathbf{E}_{\max} \end{cases} \tag{15}$$

TABLE 4. Four healthy states of UUV.

Notation	Description	Value
$\boldsymbol{S}_1$ (Well)	Normally Working	$\boldsymbol{F}_{S_1} = 1$
$\boldsymbol{S}_2$ (Mechanical-Failure)	Propulsion failure	$\boldsymbol{F}_{S_2}$
$\boldsymbol{S}_3$ (Electronic-Failure)	Electronic failure	$\boldsymbol{F}_{S_3}$
$\boldsymbol{S}_4$ (Stopping)	Energy and health constraint	$\boldsymbol{F}_{S_4} = 0$

(2) Each individual agent $\boldsymbol{U}_i$ is in a dynamic environment, nonlinear external disturbance may directly affect motion control of hunter agent, and further interferes a bad selection in discrete behavior. Hence, we establish a fully healthy state set that can describe UUV health from the viewpoint of reliability theory [4], in which four states are illustrated in Table 4.

In Table4, $\boldsymbol{S}_1$ describes normally working with state-value $\boldsymbol{F}_{\boldsymbol{S}_1} = 1$. $\boldsymbol{S}_2$ and $\boldsymbol{S}_3$ belong to the nor-normal type with state-value $\boldsymbol{F}_{\boldsymbol{S}_2}$ and $\boldsymbol{F}_{\boldsymbol{S}_3}$, respectively, if the two values is bigger than the pre-threshold $\boldsymbol{F}^{\boldsymbol{p}}_{\boldsymbol{S}_2}$ obtained by normal-distribution and pre-threshold $\boldsymbol{F}^{\boldsymbol{p}}_{\boldsymbol{S}_3}$ obtained by exponential-distribution, respectively, UUV has ability to participate in hunting task, otherwise it can not continue to participate. And the last $\boldsymbol{S}_4$ describes failure agent with state-value $\boldsymbol{F}_{\boldsymbol{S}_4} = 0$ due to the energy and health constraint, it is implied that this agent adopts $\boldsymbol{B_S}$. Hence, if the total healthy state-value $\mathbf{H}_{\mathrm{T}}(\boldsymbol{U}_i^k)$ is lower than $\mathbf{H}_{\min} = \boldsymbol{F}^{\boldsymbol{p}}_{\boldsymbol{S}_2} \cdot \boldsymbol{F}^{\boldsymbol{p}}_{\boldsymbol{S}_3}$, this agent execrates $\boldsymbol{B_S}$, otherwise it selects $b^l \in \{\boldsymbol{B_N}, \boldsymbol{B_D}, \boldsymbol{B_C}, \boldsymbol{B_M}\}$ via behavioral-intensity. It is given at any iteration k as

$$\begin{cases} b_i^l \leftarrow \boldsymbol{B_S}, & \mathbf{H}_T(\boldsymbol{U}_i^k) < \mathbf{H}_{\min} \\ b_i^l \leftarrow \{\boldsymbol{B_N}, \boldsymbol{B_D}, \boldsymbol{B_C}, \boldsymbol{B_M}\}, & \mathbf{H}_T(\boldsymbol{U}_i^k) \geq \mathbf{H}_{\min} \end{cases} \tag{16}$$

$$\mathbf{H}_T(\boldsymbol{U}_i^k) = \boldsymbol{F}_{S_1}(k) \cdot \boldsymbol{F}_{S_2}(k) \cdot \boldsymbol{F}_{S_3}(k) \cdot \boldsymbol{F}_{S_4}(k) \tag{17}$$

3) BEHAVIOR-DRIVEN GLOBAL CONTROL UNDER CONSTRAINTS

Under energy consumption and healthy state constraints, core algorithm of the proposed behavior-driven global searching control is shown as Table.5.

B. LOCAL CONTROL FOR TRACKING AND CAPTURING

In this paper, it is a critic time-point when an target is detected by global searching network $\boldsymbol{N_G}$, because it is an important trigger that drive forming of local network $\boldsymbol{N_L}$ to track and capture target as shown in Fig.14, that is, $\boldsymbol{N_G}$ is divided into several $\boldsymbol{N_L}$ due to the number of target, and emergence of $\boldsymbol{N_L}$ can be synchronous or asynchronous. It is noting that this explanation is consistent with the implied by the proposed hybrid non-central distributed topology as demonstrated in Fig.11 and Fig.12.

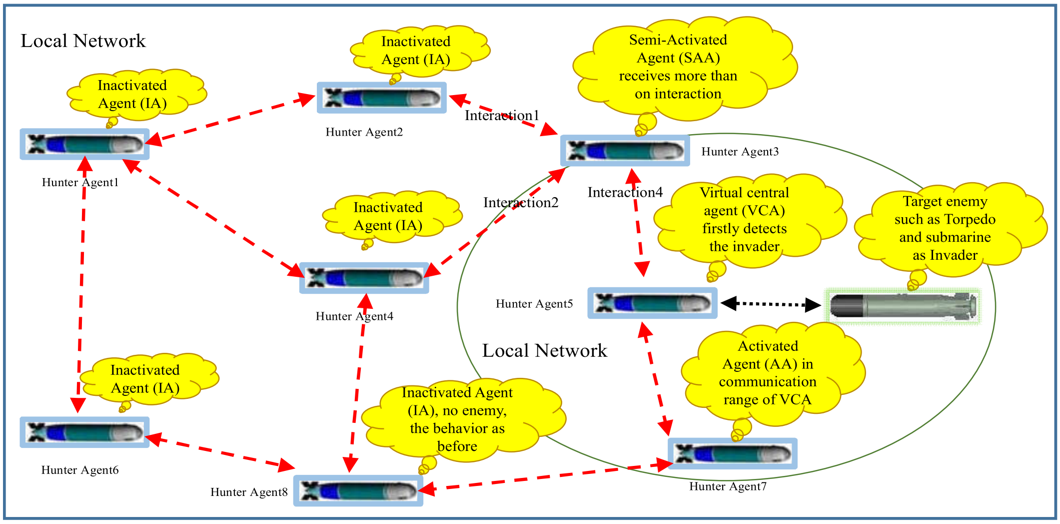

FIGURE 14. Agents in local network.

TABLE 5. Behavior-driven global control under constraints.

Input: Agent $U_i \in [U_1, U_2, \cdots, U_N]$, Behavior $b^l \in [B_S, B_N, B_D, B_C, B_M]$
Output: A global network N_G of agent associated individual optimal behavior b_{op}
Initialize: B_N for each agent, Detection Range D_R, Communication Range C_R, Maximum number of iterations K, and related variables

While A N_G is not satisfied or the iteration number not reach to K **do**
$k \leftarrow 0$
For any agent U_i derived form $[U_1, U_2, \cdots, U_N]$
Global network evolution via behavioral-intensity
• Calculating Ω_1 of stimulation among agents by Eq.(9)
• Calculating Ω_2 of stimulation of interference model by Eq.(10)
• Calculating Ω_3 of stimulation of absence of behavior interaction by Eq.(11)
Return updating N_G by Eq.(8) or Eq.(12)
• Calculating behavior energy and healthy status constraints by Eq.(15) and Eq.(16)
Else keeping original B_N for each agent in global network N_G
$k \leftarrow k+1$
Repeat

Due to the target is detected by N_G, behavioral-intensity of each hunter agents can significantly change compared with that of N_G. Thus, we need to consider target-stimulus in global control of Eq.(12) when hunting alliance is dynamically evolving. Hence, Ω_4 denotes the behavioral-intensity that is derived from target-stimulus, it is defined as

$$\Omega_4(t) = \sum_{j=1}^{W_i} \Phi_{ij} b_i^l(t) \cdot T_{ij}(t) \tag{18}$$

where $j = 1,2,\ldots,W_i$, W_i denotes the community of targets $T_j \in [T_1, T_2, \cdots, T_{W_i}]$ detected in detection range of i-th hunter agent, Φ_{ij} is a stimulation function of l-th behavior on i-th hunter agent and j-th target associated with intensity $T_j(t)$. Moreover, the total targets are $W = \sum_{i=1}^{N} W_i$.

Accordingly, behavior-driven local control for tracking and capturing based on global control is given as

$$\dot{\Omega}(t) = \kappa_1[\Omega_1(t) + \Omega_2(t) + \Omega_4(t)] - \kappa_2\Omega_3(t) \tag{19}$$

Although, this local control is adaptive and robustness under constraints, there exists two problems, behavior aggregation and behavior selection, are needed to be mainly considered, which are all affect efficiency and robustness.

1) BEHAVIORAL-INTENSITY CONTROL STRATEGY FOR BEHAVIOR AGGREGATION

For target hunting in UIS, if local control approach is directly employed, more hunter agents will be crowded by executing the same behavior, which can cause behavioral aggregation in tracking and capturing process. Furthermore, some early experiments have reported that swarm size should not be too large, it is easy to induce resource waste and computing explosions [4], [6], [20], [22], [25], [41]. Hence, a behavioral-intensity control strategy which is inspired by clonal selection theory, is developed to flexibly determine which intensity value is maintained. It can prevents that many agent execute the same behaviors in N_L.

Clonal selection theory states that once a B-cell is activated and proliferated into plasma cells and memory cells so that adequate immune response could be accumulated, in which plasma cell can secrete specific antibodies and memory cell can dominate in the host for a long time [41]. In this process, T-cell responses to regulate antibody concentration when antigen have successfully been eliminated. If the immune response is stronger for big antigen, T-cell needs to facilitate the size of antibodies derived from B-cell and memory cell. In contrast, T-cell can restore the antibodies concentration to the initial state. Thus, the antibody concentration is more adaptive to external changing due to the function of the T-cell.

Similarly, we mimic the adaptive capability of T-cell, the concentrate of T-cell as a adjusted parameter can control behavioral-intensity to coordinate the collective behaviors in Eq.(17). Thus, Ω_5 is defined as the behavioral-intensity that is derived from T-cell adjusting in responding to the target stimulus, which is given

$$\dot{\Omega}_5(t) = \boldsymbol{\vartheta}(1\text{-}\Omega_2(t))\Omega(t) \tag{20}$$

where Ω and Ω_2 are same with Eq.(19). The $\boldsymbol{\vartheta}$ denotes a control constants associated with threaten factor, each target such as the typical large shape and small shape corresponds to specific value that is empirically defined as

$$\boldsymbol{\vartheta} = \begin{cases} \dfrac{1}{1+e^{-0.5}}, & \text{Large-shape} \\ \dfrac{1}{1+e^{0.5}}, & \text{Small-shape} \end{cases} \tag{21}$$

Therefore, Eq.(19) driven model of local control is rewritten as

$$\dot{\Omega}(b_i^l(t)) = \boldsymbol{\kappa_1}[\Omega_1(t) + \Omega_2(t) + \Omega_4(t) + \Omega_5(t)] - \boldsymbol{\kappa}_2\Omega_3(t) \tag{22}$$

$$\Omega(k) = \Omega(k-1) + \kappa_1[\Omega_1(k-1) + \Omega_2(k-1) + \Omega_4(k-1) + \Omega_5(k-1)] - \kappa_2\Omega_3(k-1) \tag{23}$$

2) DECISION-MAKING CONTROL FOR BEHAVIOR SELECTION

Although local control method in Eq.(23) can maintain an appropriate behavioral-intensity for targets in tracking and capturing $\boldsymbol{N_L}$, how to select an optimal behavior when the hunter agent receive several interactive requests is critic problem to be considered, for example hunter agent3 positioned at boundary of $\boldsymbol{N_L}$, receives some interactions (Interaction1, interaction2 and interaction4), as shown in Fig14. Moreover, one hunter agent is subject to constrains discussed in section V-A.2, how to model these constraints in determining whether this agent is involved in local hunting alliance, for example hunter agent4 stops due to lack of sufficient energy. In order to overcome the two problems, behavior decision-making strategy which is inspired by danger theory is put forward.

In danger theory, the recognition in terms of safe signal or danger signal from its neighboring environment is facilitated by a two-signal model, particularly a recognition signal (signal 1) and a co-stimulation signal (signal 2) as illustrated in Fig.8, in which involved DCs can be divided into three categories, such as immature DC, semi-mature DC and mature DC, and they have their respective roles. The immature DC collects the antigenic agent, semi-mature DC presents antigen to T-cell that causes T-cell-tolerance in safe environment, and mature DC becomes to completely activate B-cell and produce antibodies to eliminate the antigen. In addition, role of three kinds of DC is changing in terms of the external environment in a local area.

Inspired by danger theory, if a $\boldsymbol{N_L}$ is activated by target, all involved agents in forming this network can be similarly divided into four roles, virtual central agent, activated agents, semi-activated agents and inactivated agent, which are illustrated as Fig.14. The related definitions and their behavior decision-making strategy are listed as follows.

Virtual central hunter agent (VCHA)$\boldsymbol{U_{VCHA}}$ is a hunter agent $\boldsymbol{U}_i$ that firstly detects any target via $\boldsymbol{B_N}$ in its $\boldsymbol{D_R}$, and it has capable of broadcasting target information by $\boldsymbol{B_C}$ to its neighbors in its $\boldsymbol{C_R}$ for tracking target, and then its behavior is changed quickly via process of $\boldsymbol{B_M} \leftarrow \boldsymbol{B_C} \leftarrow \boldsymbol{B_D} \leftarrow \boldsymbol{B_N}$ with the highest priority listed in Table1. There is an important note that $\boldsymbol{U_{VCHA}}$ is not similar with top-down functionality of central node in centralized control [39], [40], it only plays a role of inflammation-bridge to form $\boldsymbol{N_L}$, which is the same with agent 01 or agent 02 in hybrid no-central distributed topology shown in Fig.12. For any one $\boldsymbol{U_{VCHA}}$, its decision-making strategy is implemented with iteration sequence as

$$\text{IF } \boldsymbol{U_{VCHA}}, \quad \text{THEN } b_i^l \leftarrow \boldsymbol{B_M} \leftarrow \boldsymbol{B_C} \leftarrow \boldsymbol{B_D} \leftarrow \boldsymbol{B_N} \tag{24}$$

Activated hunter Agent (AHA) $\boldsymbol{U_{AHA}}$ is the agent $\boldsymbol{U}_j$ that is in the $\boldsymbol{C_R}$ of $\boldsymbol{U_{VCHA}}, j = 1, 2, \ldots, \boldsymbol{N}_i$, $\boldsymbol{N}_i$ denotes community of agent in communication range of $\boldsymbol{U}_i$. This is that $\boldsymbol{U_{AHA}}$ is automatically assigned to the activated role with $\boldsymbol{B_M}$ as long as it is in $\boldsymbol{C_R}$, even receiving more than one behavior interaction requests. For any one $\boldsymbol{U_{AHA}}$, its behavior decision-making strategy is implemented as

$$\text{IF } \boldsymbol{U_{AHA}}, \quad \text{THEN } b_j^l \leftarrow \boldsymbol{B_M} \leftarrow \boldsymbol{B_N} \tag{25}$$

Semi-activated hunter agent (SAHA)$\boldsymbol{U_{SAHA}}$ is a agent $\boldsymbol{U}_j$ that receive some interactive requests at $\boldsymbol{C_R}$ boundary of i-th agent, behavior $b_j^l \in [\boldsymbol{B_S}, \boldsymbol{B_N}, \boldsymbol{B_D}, \boldsymbol{B_C}, \boldsymbol{B_M}]$ with maximum $\Omega_{\max}$ is selected to be executed. Moreover, if two behavioral-intensity $\boldsymbol{b}_j^l$ and $\boldsymbol{b}_j^h$ are equal, $l \neq h$, the behavior with higher priority is selected in terms of Table1. For any one $\boldsymbol{U_{SAHA}}$, its behavior decision-making strategy is implemented as

$$\text{IF } \boldsymbol{U_{SAHA}}, \text{THEN} \boldsymbol{b}_j^l \leftarrow \{\boldsymbol{B_S}, \boldsymbol{B_N}, \boldsymbol{B_D}, \boldsymbol{B_C}, \boldsymbol{B_M}\} \text{ with } \Omega_{\max} \tag{26}$$

$$\text{IF } \boldsymbol{U_{SAHA}}, \Omega_{\max}(b_j^l) = \Omega_{\max}(b_j^h), \quad \text{THEN} \begin{cases} b_j^l, & \boldsymbol{P}^l > \boldsymbol{P}^h \\ b_j^h, & \boldsymbol{P}^h > \boldsymbol{P}^l \end{cases} \tag{27}$$

Inactivated hunter Agent (IHA) $\boldsymbol{U_{IHA}}$ is a agent $\boldsymbol{U}_j$ that is outside the $\boldsymbol{N_L}$ formed by the i-th agent, $j = 1,2,\ldots\boldsymbol{N}\text{-}\boldsymbol{N}_i$, and $\boldsymbol{N} - \boldsymbol{N}_i = \{j|\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} > \boldsymbol{C_R}\}$, such as the agent2 and agent8. Its behavior stays the same as before. Thus, for any one $\boldsymbol{U}_j^{IHA}$, its behavior decision-making strategy is implemented as

$$\text{IF } \boldsymbol{U_{IHA}}, \quad \text{THEN} b_j^l \leftrightarrow \boldsymbol{B_N} \tag{28}$$

3) LOCAL BEHAVIOR-DRIVEN CONTROL UNDER CONSTRAINTS

Base on the behavioral-intensity control strategy and behavior selecting decision-making strategy, local control approach for tracking and capturing is developed under constraints, the core algorithm is overall demonstrated as Table.6.

Up to now, the global control for searching and local control for tracking and capturing are overall integrated to coordinate the collective behavior in target hunting.

VI. EXPERIMENT AND PERFORMANCE EVALUATION

To evaluate the feasibility and effectiveness of the proposed behavior-driven coordination control for target hunting by UIS in unknown and uncertain environment, some simulation experiments are conducted in MATLAB and C++ Platform, and uses the computer with Intel(R) Core^{TM}i7 CPU3.20GHz. In experiments, $[\boldsymbol{U_1}, \boldsymbol{U_2}, \cdots, \boldsymbol{U_N}]$ of N=25 hunter agents is given a task to hunt some targets $[\boldsymbol{T}_1, \boldsymbol{T}_2, \cdots, \boldsymbol{T_W}]$, $\boldsymbol{W}$=1 or $\boldsymbol{W}$=3, and all hunter and targets are subject to their assumptions in Section II, and the dynamics of each heterogeneous UUV is based on Eq.(6) [48]. The velocity of hunter agent is greater than the velocity of target in order to successfully capture, so a half of hunter agents have lower velocity that may be same as the target, and the other half are faster than the target by the 20% empirically. And, the mark of successful capturing is that eight hunter agents can track the invaded target in a local hunting alliance. Inspired by distributed control for UAV swarm coordination [43], all experiments are divided into for two cases: initial positions are fixed distribution and random distribution, which are demonstrated as Fig.15.

The parameters in all experiments are set as: 2-D underwater environment with 10000 × 10000, $\boldsymbol{D_R} = 1800$, $\boldsymbol{C_R} = 2400$, $\boldsymbol{T_R} = 2000$, $\boldsymbol{\kappa_1} = 0.85$, $\kappa_2 = 0.15$, $\boldsymbol{K}$=200, $g = 1.5$, $\Delta = 0.2$, $\sigma = 0.6$, $\mathbf{E}_{\max} = 0.8$, $\boldsymbol{F}^{\boldsymbol{p}}_{S_2} = 0.70$, $\boldsymbol{F}^{\boldsymbol{p}}_{S_3} = 0.72$, $\mathbf{H}_{\min} = 0.50$, $\boldsymbol{\vartheta} = 0.622$(small-shape), $\Phi_{ij} = 1$, and Θ_{lh} is shown as Table.7. Notion that all above parameters are all regularization.

A. BEHAVIOR-DRIVEN COORDINATION CONTROL OF CASE 1

(1) A scenario of hunting for target $\boldsymbol{W}$=1 is designed as: Hunter agents is conducted with $\boldsymbol{N}$=25, initial location of hunter agent is the same with the exhibited in Fig.15(a), and its heading angle ψ is given randomly. The target is asynchronously introduced at position of (8000,5000), and its heading angle is $\psi_T = -\pi$. The processing is illustrated in Fig.16 and Fig.17.

Fig.16 demonstrates searching, tracking and capturing stages of target hunting. In initial searching stage, each hunter agent is configured the initial $\boldsymbol{B_N}$ behavior to establish a global searching network that is utilized to detect potential target in unknown environment, as shown in Fig.16(a) at 50th iteration. In the tracking stage, a target denoted as dotted rectangle appears at location (8000,5000) with $\psi_T = -\pi$ in Fig.16(b). Then, the nearby 23th hunter agent firstly detects it, the global network is divided, and the target adopts the second escaping strategy from the mid-point

TABLE 6. Behavior-driven local control under constraints.

Input: Hunter agent $\boldsymbol{U}_i \in [\boldsymbol{U}_1, \boldsymbol{U}_2, \cdots, \boldsymbol{U}_N]$, Target $\boldsymbol{T}_j \in [\boldsymbol{T}_1, \boldsymbol{T}_2, \cdots, \boldsymbol{T}_W]$, Behaviors $b^l \in [\boldsymbol{B}_S, \boldsymbol{B}_N, \boldsymbol{B}_D, \boldsymbol{B}_C, \boldsymbol{B}_M]$
Output: A local network $\boldsymbol{N}_L$ of agent associated individual optimal behavior b_{op}
Initialize: $\boldsymbol{B}_N$ for each agent, Detection Range $\boldsymbol{D}_R$, Communication Range $\boldsymbol{C}_R$, Maximum iterations $\boldsymbol{K}$, Maximum threshold $\mathbf{E}_{\max}$, Minimum threshold $\mathbf{H}_{\min}$, and related variables

While A $\boldsymbol{N}_L$ is not satisfied or the maximum iterations not reach to $\boldsymbol{K}$ **do**
For any agent $[\boldsymbol{U}_1, \boldsymbol{U}_2, \cdots, \boldsymbol{U}_N]$
• $k \leftarrow 0$
• Detection targets $[\boldsymbol{T}_1, \boldsymbol{T}_2, \cdots, \boldsymbol{T}_W]$ (Existing or Not existing).
If any $\boldsymbol{T}_j$ is detected by any $\boldsymbol{U}_i$ with detection range $\boldsymbol{D}_R$
• Forming $\boldsymbol{N}_L$
• Role division into $\boldsymbol{U}_{VCHA}$, $\boldsymbol{U}_{AHA}$, $\boldsymbol{U}_{SAHA}$, $\boldsymbol{U}_{IHA}$ within communication range $\boldsymbol{C}_R$
IF $\boldsymbol{U}_i \in \boldsymbol{U}_{VCHA}$
Local network $\boldsymbol{N}_L$ evolution via behavioral-intensity by Eq.(22) or Eq.(23)
▪ Implementing decision-making control for behavior selection $b_{op} = b_i^l$ by Eq.(24)
▪ Calculating behavior energy and healthy status constraints by Eq.(15) and Eq.(16)
End IF $\boldsymbol{U}_j \in \boldsymbol{U}_{AHA}$
Local network $\boldsymbol{N}_L$ evolution via behavioral-intensity by Eq.(22) or Eq.(23)
▪ Implementing the decision-making strategy of selecting $b_{op} = b_j^l$ behavior by Eq.(25)
▪ Calculating behavior energy and healthy status constraints by Eq.(15) and Eq.(16)
End IF $\boldsymbol{U}_j \in \boldsymbol{U}_{SAHA}$
Local network $\boldsymbol{N}_L$ evolution via behavioral-intensity by Eq.(22) or Eq.(23)
▪ Implementing the decision-making strategy of selecting $b_{op} = b_j^l$ behavior by Eq.(26) and (27)
▪ Calculating behavior energy and healthy status constraints by Eq.(15) and Eq.(16)
End IF agent $\boldsymbol{U}_j \in \boldsymbol{U}_{IHA}$
Local network $\boldsymbol{N}_L$ evolution via behavioral-intensity by Eq.(22) or Eq.(23)
▪ Implementing the decision-making strategy of selecting $b_{op} = b_j^l$ behavior by Eq.(28)
▪ Calculating behavior energy and healthy status constraints by Eq.(15) and Eq.(16)
End
Else keeping original $\boldsymbol{B}_N$ for each agent in global network $\boldsymbol{N}_G$
• $k \leftarrow k+1$
Repeat

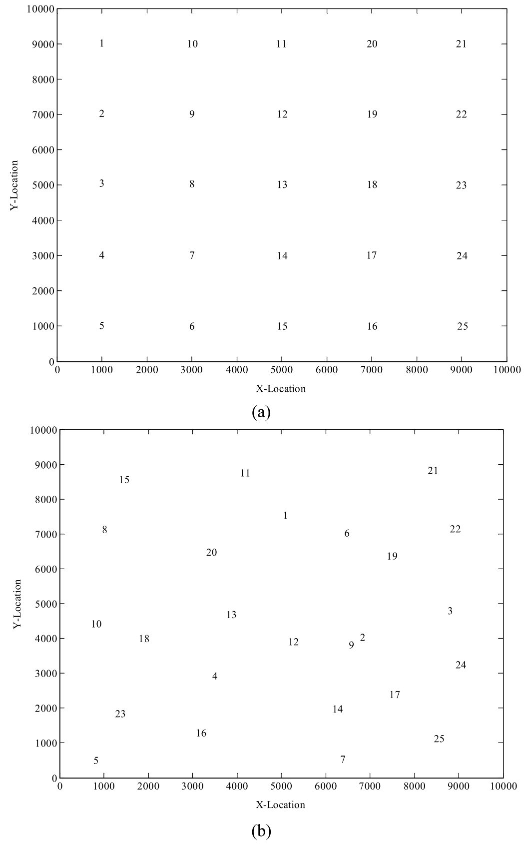

FIGURE 15. Initializing position. (a) Case1 for fixed distribution. (b) Case2 for random distribution.

TABLE 7. Matching function Θ_{lh}.

$b^l \setminus b^h$	B_S	B_N	B_D	B_C	B_M
Stopping, B_S	1	-0.2	-0.2	-0.2	-0.3
Navigating, B_N	-0.3	1	-0.3	-0.3	-0.6
Detecting, B_D	-0.2	-0.3	1	-0.3	-0.5
Communicating, B_C	-0.2	-0.3	-0.3	1	-0.4
Moving, B_M	-0.3	-0.6	-0.5	-0.4	1

of agent18 and agent17. Further, local network of hunting alliance continuously form, as shown in Fig.16(c) at 150th iteration. In capturing stage, the target is captured by hunter alliance $[U_{11}, U_{12}, U_{13}, U_{18}, U_{19}, U_{22}, U_{23}, U_{24}]$ at position (5100,6100) until 200 iterations. In this hunting process, hunter agents search, track and capture the target efficiently with the guidance of the proposed behavior-driven coordination control framework.

Fig.17 shows the priority P^l changes for typical agents during the hunting process in this situation. The hunter agent23 firstly detects target, which has a role of U_{VCHA} that is responded to broadcast target information in its communication range, then rapidly coordinate an local hunting alliance to track and capture, and its behavior changes is

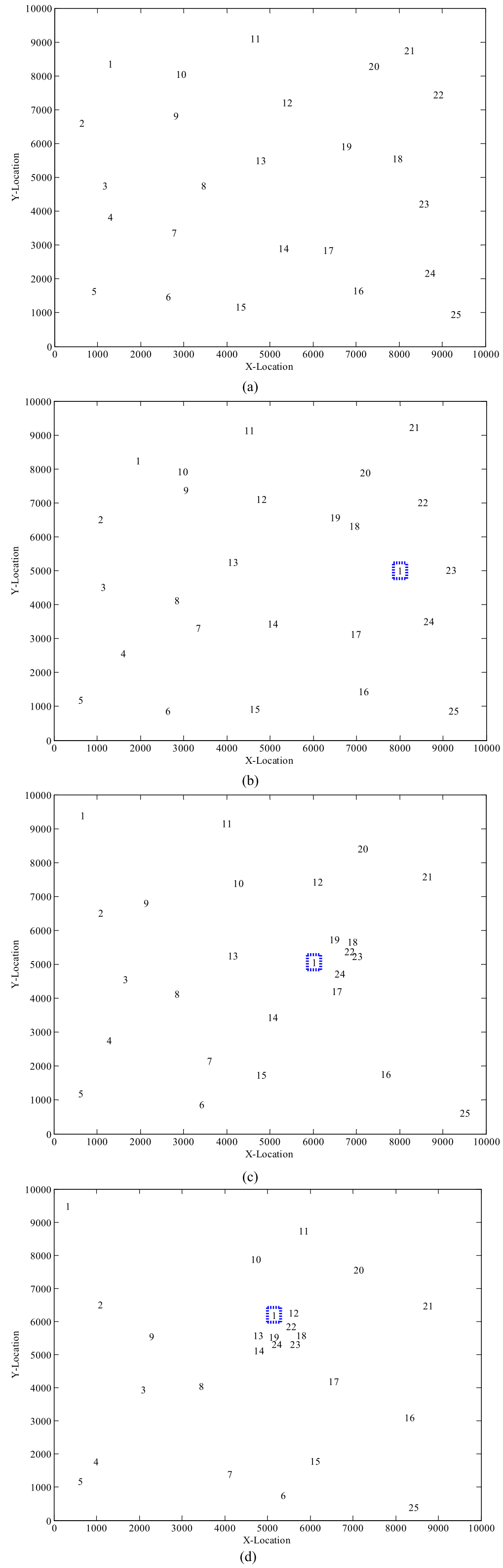

FIGURE 16. Hunting processing for target $W = 1$ by using 25 hunter agents. (a) Searching target at 50th iterations, (b) appearing target at 100th iterations, (c) tracking target at 150th iterations and (d) capturing target at 200th iterations.

$B_M \leftarrow B_C \leftarrow B_D \leftarrow B_N$ at 90-th, 91-th and 92-th iteration, respectively. The hunter agent12 is subject to external

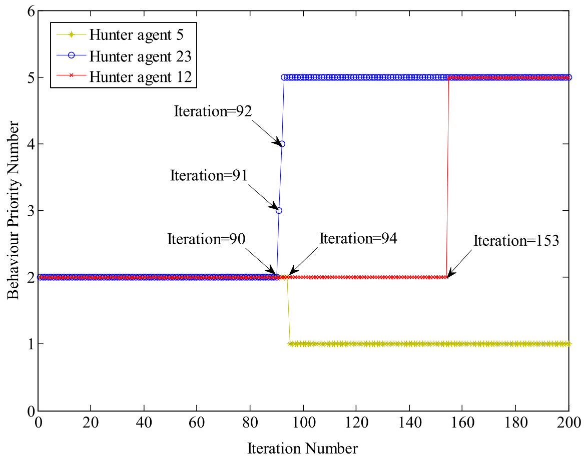

FIGURE 17. Changes of behavior priority of typical hunter agents (5,12, and 23).

disturbance until 153-th iteration, its behavioral-intensity satisfies for $\boldsymbol{B_M}$ activation. Especially for hunter agent5, it executes the behavior $\boldsymbol{B_S}$ with lowest priority at the 94-th iteration, which also can be seen in Fig.16(c)~(d), it is the reason that this agent is failure due to the $\boldsymbol{S}_3$ healthy state. It is implied that the proposed framework has great robustness in forming the hunting alliance under uncertain constraints. In addition, due to the longer distance, hunter agents, such as agent 1 and agent 2, do not receives any stronger interaction implied by behavioral-intensity, so the behavior aggregation is effectively avoided and each individual hunter agents can elaborately make decision to select its optimal behavior.

(2) A scenario of hunting for three targets $\boldsymbol{W}$=3 is designed as: Hunter agents is conducted with $\boldsymbol{N}$=25, initial location of each hunter agent is the same with the exhibited in Fig.15(a), and its heading angle ψ is given randomly. The target is asynchronously introduced at positions of (5500,8000) with $\psi_T = 0$, (7800,4600) with $\psi_T = -\pi$ and (2000,2000)with $\psi_T = 0$, respectively. Hunting processing is illustrated in Fig.18.

Fig.18 demonstrates the hunting process for three targets denoted as dotted rectangle1, 2 and 3. In initial stage, the global network composed of 25 hunter agents is configured to search targets. Three targets are asynchronously introduced at 90th, 100th and 110th iteration, which are firstly detected by 12th, 24th and 4th hunter agents, respectively. It is implied that the global searching network is divided into three hunting alliance of local networks to track and capture, as shown in Fig.18(c). Finally, targets are captured by alliances $[\boldsymbol{U_9}, \boldsymbol{U_{10}}, \boldsymbol{U_{11}}, \boldsymbol{U_{12}}, \boldsymbol{U_{19}}, \boldsymbol{U_{20}}, \boldsymbol{U_{21}}, \boldsymbol{U}_{22}]$, $[\boldsymbol{U_{13}}, \boldsymbol{U_{14}}, \boldsymbol{U_{16}}, \boldsymbol{U_{17}}, \boldsymbol{U_{18}}, \boldsymbol{U_{23}}, \boldsymbol{U_{24}}, \boldsymbol{U}_{25}]$ and $[\boldsymbol{U}_2, \boldsymbol{U}_3, \boldsymbol{U}_4, \boldsymbol{U}_5, \boldsymbol{U}_6, \boldsymbol{U}_7, \boldsymbol{U}_8, \boldsymbol{U}_{15}]$ at position (7000,8400), (5500, 4800) and (3200,1200) as shown in Fig.18(d), respectively. In this hunting process, the excluded agent1 adopts $\boldsymbol{B_S}$ due to without receiving any interactive request from any $\boldsymbol{N}_L$, since it locals outside $\boldsymbol{C_R}$ of any $\boldsymbol{U_{VCHA}}$.

Furthermore, the hunting alliances for three targets are distinguished and successful, there is no overlap behavior aggregation, each hunter agent can adopt its optimal behavior in different stage of searching, tracking and capturing, which can be seen the changes of behavior priority $\boldsymbol{P}^l$ of typical hunter agents (1, 2, 4, 12 and 24) in Fig.19, where hunter agent 4, 12 and 24 all plays the role of $\boldsymbol{U_{VCHA}}$ to form the hunting alliance in local network, and agent 2 plays the role of $\boldsymbol{U_{SAHA}}$ to participate the third hunting alliance at 153th iteration, and agent 1 is a failure at 122th iteration, the reason is that agent 1 rapidly exceeds energy consumption due behavior $\boldsymbol{B_N}$ and its-self smaller energy capacity. From the above results, switching process of global control and local control is effective and smooth, it is implied that proposed framework works with great robustness and fault-tolerance in this intelligent swarm.

B. BEHAVIOR-DRIVEN COORDINATION CONTROL OF CASE 2

A scenario of hunting for target is designed as: Hunter agents is conducted with $\boldsymbol{N}$=25 to hunt target $\boldsymbol{W}$=1 and $\boldsymbol{W}$=3, respectively. The initial location of hunter agent is the same with the exhibited in Fig.15(b), and its heading angle ψ is given randomly. The $\boldsymbol{W}$=1 is introduced at the position of (8000,5000), and its heading angle is $\psi_T = -\pi$. While $\boldsymbol{W}$=3 are asynchronously introduced at positions of (5500,8000) with $\psi_T = 0$, (7800,4600) with $\psi_T = -\pi$ and (2000,2000) with $\psi_T = 0$, respectively. Hunting processing for $\boldsymbol{W}$=1 and $\boldsymbol{W}$=3 are illustrated in Fig.20.

The results for hunting in manner of random distribution are demonstrated in Fig.20. From the Fig.20(a)~(c), we can see that all the hunter agents work properly for tracking and capturing the only one target by the proposed control framework, even in the presence of agent failure such as the agent18 due to the healthy constraints, and other agents excluded in local hunting alliance are able to autonomously navigate and search the potential targets, it is driven by the behavioral-intensity of all involved agents. From Fig.20(d)~ (f), three asynchronous targets separate the global searching network into three local networks, all of which are driven by hunting alliances in unknown environment even the failure agent15. It is confirmed that proposed framework is capable of completing target hunting in case of unknown and uncertain failures.

From the results of two cases in Fig.16-20, it is exhibited that the proposed behavior-driven coordination control framework can work efficiently and satisfactorily whither different constraints or target number, even some hunter agents can be unavailable. The reason behind these results are the flexible hybrid topology and excellent coordination control.

C. COMPARISON WITH OTHER METHODS

In order to evaluate the performance of the proposed framework, some compared experiments are implemented with four prevalent methods, which are the centralized coordination based leader-follower (CCLF) [44], CNP negotiation method (CNP) [45], immune-network model (INM) [46] and behavior-based swarm intelligence (BSI) [43], where CCLF is a centralized method with a star-like topology, CNP is a

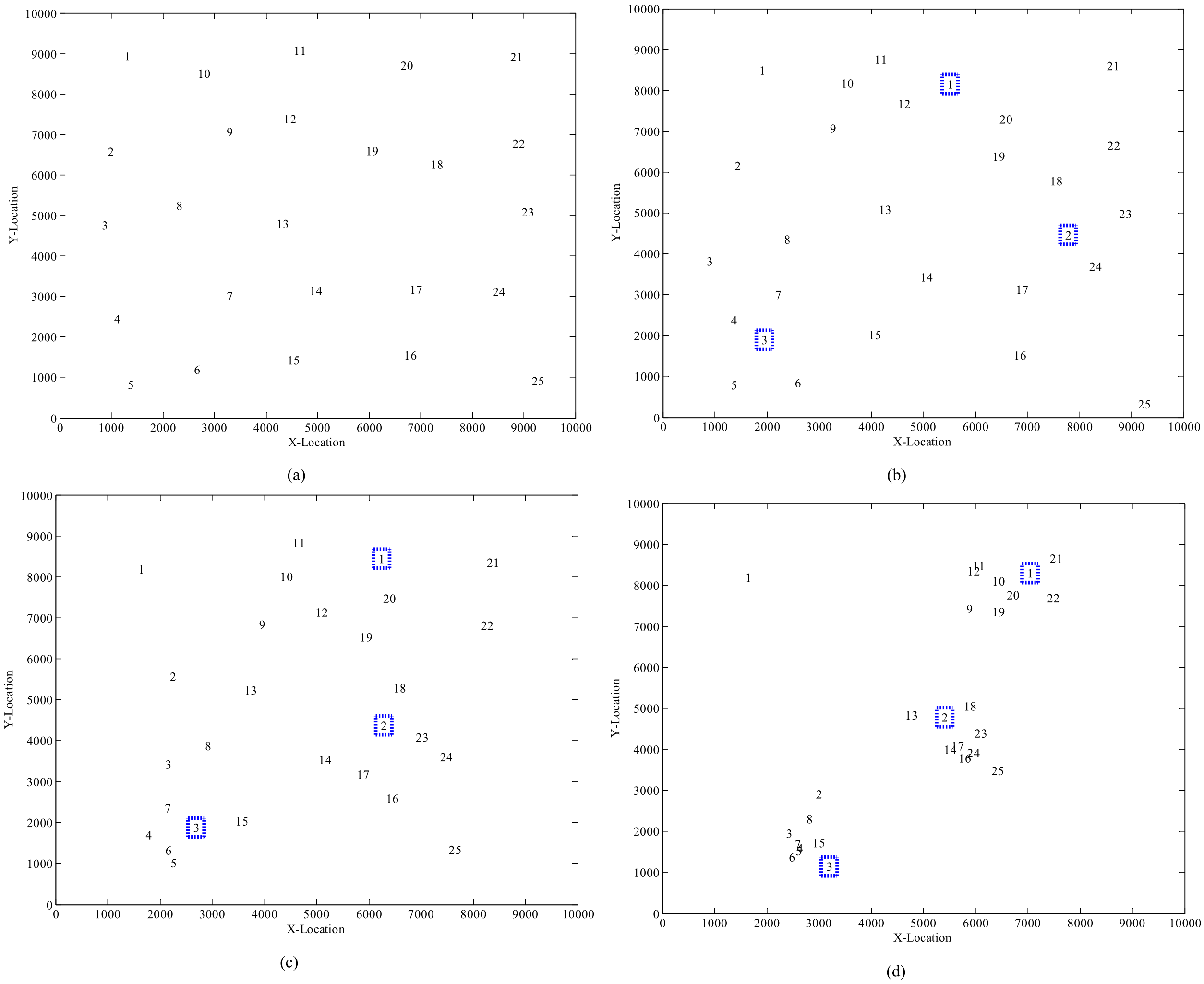

FIGURE 18. **Hunting processing for target $W = 3$ by using 25 hunter agents. (a) Searching target at 50th iteration, (b) targets asynchronously appearing, (c) tracking target and (d) capturing target.**

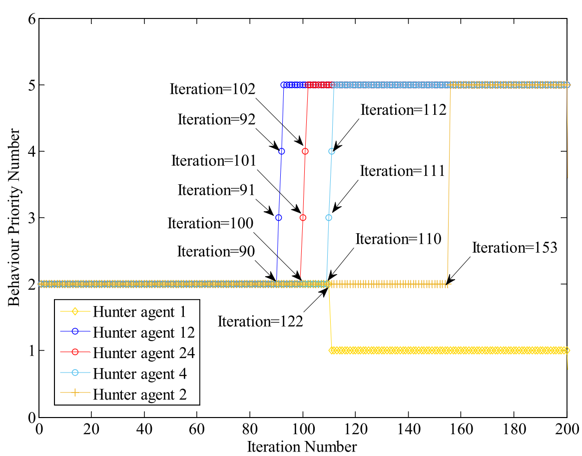

FIGURE 19. **Changes of behavior priority of typical hunter agents (1, 2, 4, 12 and 24).**

distributed method with a star-like topology, and INM is a distributed method with a web-like topology, and BSI is a distributed method with a hybrid topology, and our proposed framework adopts a distributed control with a hybrid non-central topology.

Moreover, three quantitative performance indicators are defined to evaluate the effectiveness and efficiency of these comparative methods. (1) Hunting time (HT) is defined as a time elapsed via iteration number in hunting process, which contains any iterations spending on searching and tracking until capturing successfully. (2) Energy consumption (EC) is defined to evaluate the cost of behavior-driven coordination processing under uncertain constraint. And (3) hunting distance (HD) is defined to measure the movement distance from the initial iteration. Generally, a lower value of those indicators implies that hunting process is of greater robustness and efficiency.

The comparative experiments are implemented with the same configuration of Section VI-A and Section VI-B for five methods, which exists four different experiments, (i) case 1 for W=1, (ii) case 2 for W=1,(iii) case 1 for W=3, and (iv) case 2 for W=3. The five methods are conducted on the same experiments, all compared results based on performance indicators are illustrated in Fig.21. Moreover, the same experiments repeated 50 times for all five methods are further conducted to prove the robust performance of

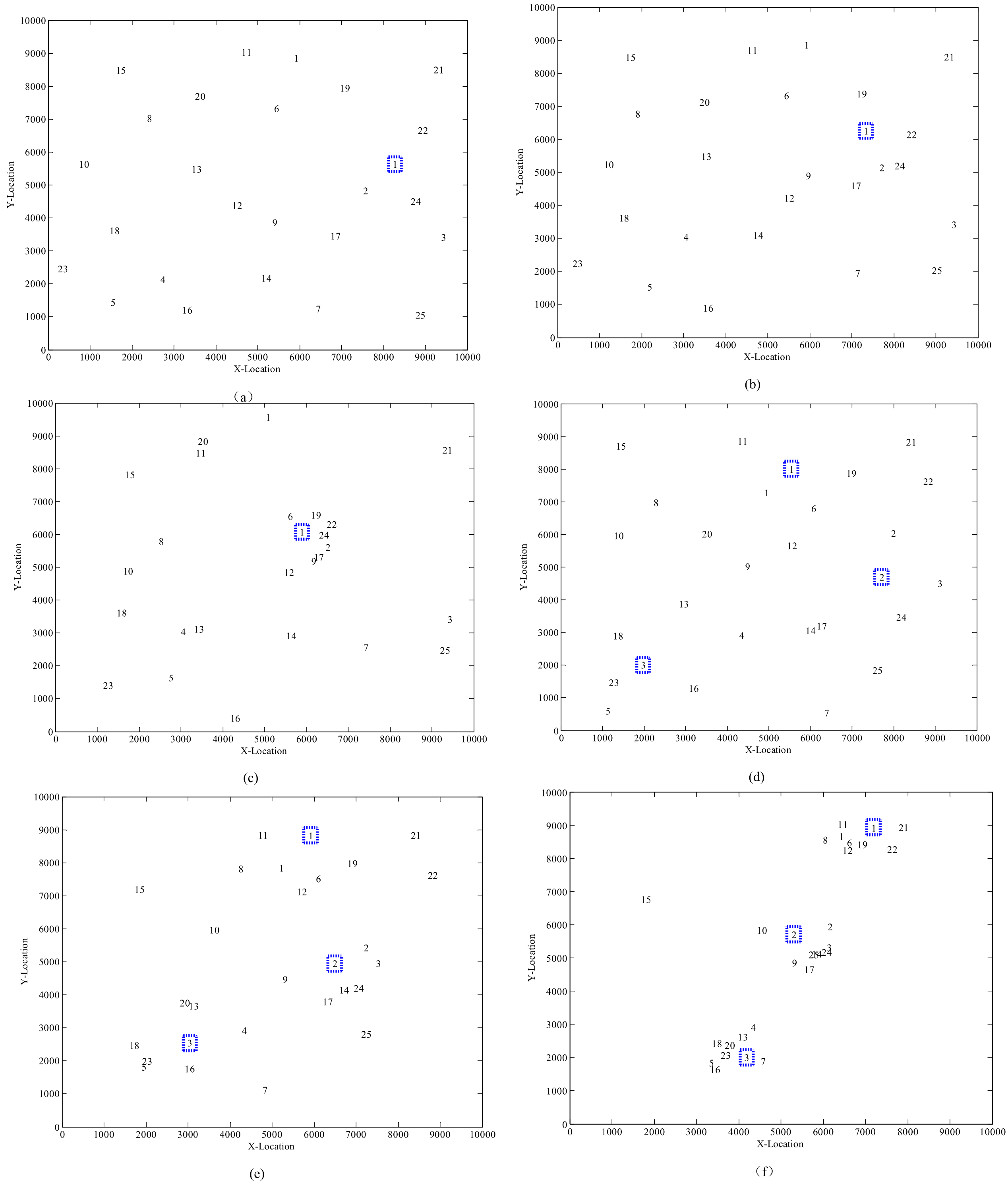

FIGURE 20. **Hunting process, in which (a), (b) and (c) are for target $W = 1$, while (d), (e) and (f) are for targets $W = 3$. (a) and (d) Appearing target at 100th iteration, (b) and (e) tracking target at 150th iteration, and (c) and (d) capturing target at 200th iteration.**

our proposed framework, compared results of average and standard deviation are exhibited in Table 8∼12.

As shown in Figs.21, three quantitative performance indicators of case 2 are higher than that of case 1, it is implied that random distribution has a greater affect on the forming local hunting alliance, especially for the detecting and communication of tracking stage. Moreover, those comparative indicators for targets W=3 is higher than that of target W=1, this is because that the vale of behavioral-intensity is improving with increasing of target number. However, the increase of the proposed method is the least.

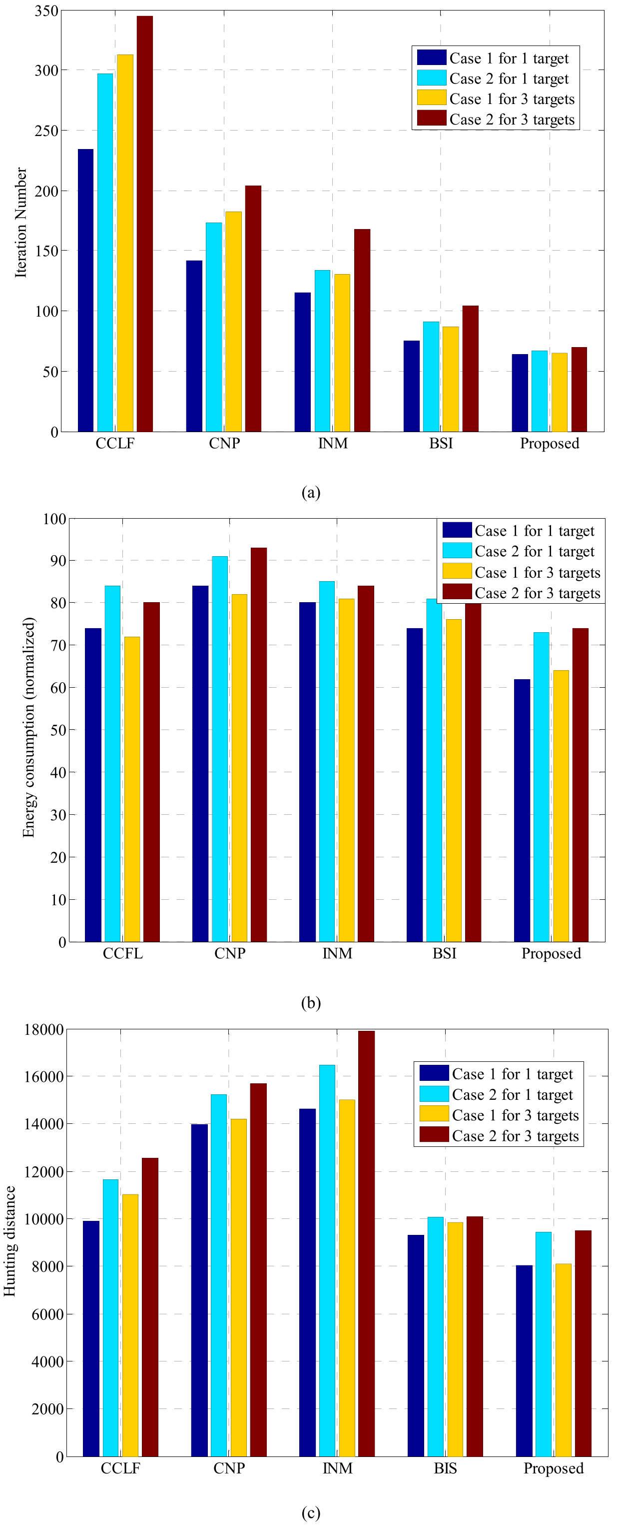

FIGURE 21. **Comparison results. (a) HT, (b) EC, and (c) HD.**

Among the five methods, the proposed method works with the highest efficiency in different cases and target numbers. In terms of HT, the largest value of CCFL compared with others methods is demonstrated in Fig.21(a), one reason why it costs much time is that it adopts a centralized coordination control with an star-like topology. If some agents are not available due to constraints, the more time is needed to reconfigure the centralized architecture. In terms of EC, although CNP based on market mechanism is a distributed coordination method with star-like topology, the most energy in Fig.21(b) is consumed in comparison with that of others, because there exists a great mount of mutual interaction and communication between contractor and administrator [4], [28], especially when the new target is added. In terms of HD, INM exists an hunting process with the longest distance in Fig.21(c), especially for targets $\boldsymbol{W}$=3, in which control parameters are not fully considered due to complete graph of all agents, much agents undergoes invalid motion.

Furthermore, performance of BSI and proposed method are better than others three methods, which exhibits the great efficiency of behavior-based distributed coordination control with hybrid topology. However, BSI can not well deal with the problems of behavior aggregation and uncertain constraints, which result in a bigger energy consumption and hunting distance. Additionally, the results in Fig.21 demonstrates that the proposed method is not very sensitive to the variations of the case and target number, which also prove adaptability and robustness for dynamic environments.

Table 8∼9 displays average value of HT, EC and HD in 50 repeated experiments with aforementioned five methods. It is indicated that our proposed method achieves the lowest HT, EC and HD performance under different cases. Table 10∼11 displays the standard deviation of HT, EC and HD, the standard deviation of their method is much larger than that of our proposed methods, especially for HT of CCLF, EC of CNP, and HD of INM. It is shown that the stability and robustness of our proposed is stronger than that of other methods.

In order to further prove differences of observed average value in Table 8∼9 are significant or not, an Analysis of variance (ANOVA) is employed to determine whether the mean of subjects are different, and it uses the F-test to statistically test the equality of means [49]. In this paper, there are five subjects corresponding to five methods, and within subject, four types of observed average value, such as (i) case 1 for $\boldsymbol{W}$=1, (ii) case 2 for $\boldsymbol{W}$=1,(iii) case 1 for $\boldsymbol{W}$=3, and (iv) case 2 for $\boldsymbol{W}$=3 in Table 8∼9, are selected to form the sampled data set of each indicator. Moreover, all statistics are F-distributed in terms of degree of freedom (df) of Between subjects n_1 and Within subject n_2, and it can be checked in F-test threshold-table. Results are demonstrated in Table 12.

Table 12 displays analysis results of ANOVA for three indicator. F-values of three indicators listed in the sixth column are calculated as $F(\mathrm{HT}) = 14.201$, $F(\mathrm{EC}) = 3.753$ and $F(\mathrm{HD}) = 21.234$, all of which are bigger than critical value $F_{0.05(4,15)} = 3.056$ with significant level $\alpha = 0.05$. It is proved that the observed average value is significative difference in terms of HT, EC and HD, which given a stronger evidence that the proposed control framework is the most stable no matter for topology and control manner compared with the five methods.

TABLE 8. 50 comparative experiments for $W = 1$ on average value of three indicators.

Method	Topology	Control manner	HT		EC		HD	
			Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
CCLF[44]	Star-like	Centralized	239.4	296.8	73.9	83.0	9950	11640
CNP[45]	Star-like	Distributed	141.8	172.0	83.6	90.9	14031	15208
INM[46]	Web-like	Distributed	116.0	137.5	80.1	84.8	14580	16420
BSI[43]	Hybrid	Distributed	76.2	89.8	74.0	81.3	9245	10100
Proposed	**Hybrid non-central**	**Distributed**	**69.4**	**72.4**	**62.7**	**73.4**	**8052**	**9327**

TABLE 9. 50 comparative experiments for $W = 3$ on average value of three indicators.

Method	Topology	Control manner	HT		EC		HD	
			Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
CCLF[44]	Star-like	Centralized	318.6	345.7	71.7	80.2	11250	12560
CNP[45]	Star-like	Distributed	173.4	203.2	82.0	92.8	14200	15802
INM[46]	Web-like	Distributed	134.2	162.1	81.0	84.5	15004	17905
BSI[43]	Hybrid	Distributed	86.3	95.8	75.5	80.9	9850	10070
Proposed	**Hybrid non-central**	**Distributed**	**73.0**	**74.8**	**63.9**	**74.2**	**8105**	**9358**

TABLE 10. 50 comparative experiments for $W = 1$ on standard deviation of three indicators.

Method	Topology	Control manner	HT		EC		HD	
			Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
CCLF[44]	Star-like	Centralized	**4.951**	**5.218**	2.101	2.348	43.125	46.481
CNP[45]	Star-like	Distributed	3.245	3.485	**4.128**	**4.421**	45.358	47.856
INM[46]	Web-like	Distributed	2.801	2.853	2.012	2.207	**59.257**	**62.349**
BSI[43]	Hybrid	Distributed	2.781	2.950	1.954	2.143	40.128	42.982
Proposed	**Hybrid non-central**	**Distributed**	**2.529**	**2.593**	**1.829**	**1.901**	**33.584**	**36.018**

TABLE 11. 50 comparative experiments for $W = 3$ on standard deviation of three indicators.

Method	Topology	Control manner	HT		EC		HD	
			Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
CCLF[44]	Star-like	Centralized	**5.523**	**5.971**	2.694	2.864	43.517	46.582
CNP[45]	Star-like	Distributed	3.458	3.695	**4.369**	**4.528**	48.891	50.124
INM[46]	Web-like	Distributed	2.985	3.219	2.451	2.759	**67.854**	**70.125**
BSI[43]	Hybrid	Distributed	2.951	3.125	2.354	2.562	42.361	45.691
Proposed	**Hybrid non-central**	**Distributed**	**2.701**	**2.803**	**1.962**	**2.017**	**36.245**	**38.691**

TABLE 12. Analysis results of ANOVA.

Indicator	Within subject and Between subjects	Sum of Square (SS)	Degrees of freedom (df)	Mean Square (MF)	F
	Between subjects	35193.280	4	8798.320	**14.201**
HT	Within subject	9293.611	15	619.574	
	Sum	44486.891	19		
	Between subjects	227.750	4	56.938	**3.753**
EC	Within subject	227.560	15	15.171	
	Sum	455.31	19		
	Between subjects	73180517	4	18295129	**21.234**
HD	Within subject	12923749	15	861583	
	Sum	86104266	19		

Additionally, in the four distributed method (CNP, INM, BSI and Proposed), hybrid non-central topology inspired by immune mechanism in our method absorbs outstanding properties from star-like, web-like topology and its variations,

TABLE 13. **Comparisons of three topologies architecture.**

Properties	Web-like	Star-like	Hybrid	Hybrid non-central
Autonomous	High	Low	Medium	High
Adaptive	Low	High	High	High
Interactive	High	Medium	High	High
Cooperative	Low	High	High	High
Dynamic	Medium	Medium	High	High

such as autonomy, adaption, interaction, cooperation and dynamicity [39], [40], [43]. Table 13 exhibits the comparison of four different distributed coordination control. It is implied that the smooth switching is facilitated to swarm control via the hybrid non-central topology.

VII. CONCLUSIONS AND FUTURE WORKS

Coordination control of target hunting is one of primitive challenging problems in UIS. In this paper, a behavior-driven coordination control framework involved topology architecture and swarm control is proposed to realize searching, tracking and capturing in unknown and uncertain environment. By virtue of the immune mechanisms, hybrid no-central topology and dual-layer switching control scheme are developed to tightly couple, in which behavior conflict under constraints is solved by two strategies, such as behavioral-intensity control strategy for behavior aggregation and decision-making control strategy for behavior selection. Extensive simulations have been conducted to evaluate robustness and effectiveness of the proposed framework. Eventually, results have demonstrated great performance in different conditions compared with several state-of-the-art methods for centralized or distributed control of target hunting. It is confirmed the proposed framework is more suitable target hunting under dynamic underwater environment. Our future work will focus on the design of static or dynamic avoiding obstacles in target hunting in 3D underwater environment. Moreover, targets only escape independently under hunting condition in this paper, there is no considering the capability of swarm confrontation, thus the swarm confrontation of red-blue is of significance to be solved in the future.

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