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Ship Intelligent Navigation: Perception, Decision-making, and Control

An Overview of Recent Advances in Cooperative Optimized Navigation of Multiple Unmanned Surface Vehicles

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Abstract: With the leapfrog development of marine unmanned system technology, autonomous collaborative operations of multiple Unmanned Surface Vehicles (multi-USVs) have become a key approach to solving complex sea area tasks and improving operational efficiency. Despite extensive application potentials, the cooperative optimized navigation of multiple USVs faces severe challenges. These challenges primarily originate from strong dynamic disturbances and shallow-water effects in complex aquatic environments, as well as nonlinearity and model uncertainty in USV dynamics. Furthermore, multi-objective conflicts in cooperative decision-making, network communication constraints, and security threats from physical failures and malicious cyberattacks further complicate the navigation tasks. Cooperative optimized navigation of multiple USVs has received considerable attention in recent years. This article provides a systematic review of the latest research progress in autonomous cooperative optimization navigation strategies for multiple USVs. First, the three-degree-of-freedom nonlinear dynamic model of USVs and the characterization of environmental disturbances are presented. Next, core distributed optimization techniques, including multi-objective game-theoretic path planning, distributed model predictive control, and reinforcement learning in collaborative decision-making, are briefly discussed. Then, recent results on networked coordination under resource constraints and system security control, such as event-triggered mechanisms, quantization control strategies, robust anti-disturbance control, fault-tolerant control, and active defense strategies against malicious cyberattacks, are reviewed in detail. Finally, several technical bottlenecks are summarized and future trends are suggested to direct future investigations, including multi-degree-of-freedom heterogeneity, all-weather adaptability, and human-machine integration.

Keywords: Multi-USVs; Cooperative Optimization; Reinforcement Learning; Anti-disturbance Control; Malicious Cyberattacks

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1. Introduction

1.1 Research Background and Significance

As countries around the world increasingly compete for maritime rights and interests, the development and progress of marine science and technology are extremely urgent. Efficient exploitation of marine resources and the security of maritime trade routes are now strategic priorities. Driven by this need for deep technological innovations, cooperative operations using a fleet of autonomous USVs have emerged. By simulating biological swarm behaviors, these fleets dramatically enhance operational efficiency compared to single-USV missions. Such multi-USV systems provide unique capabilities for major national strategic tasks in complex maritime zones, including deep-sea scientific observation, large-scale maritime search and rescue, and sovereignty patrols. Ultimately, the leap from individual to swarm operations expands maritime perception breadth and operational depth. It holds immense strategic value for safeguarding national maritime sovereignty and advancing the "Maritime Community of Shared Future".

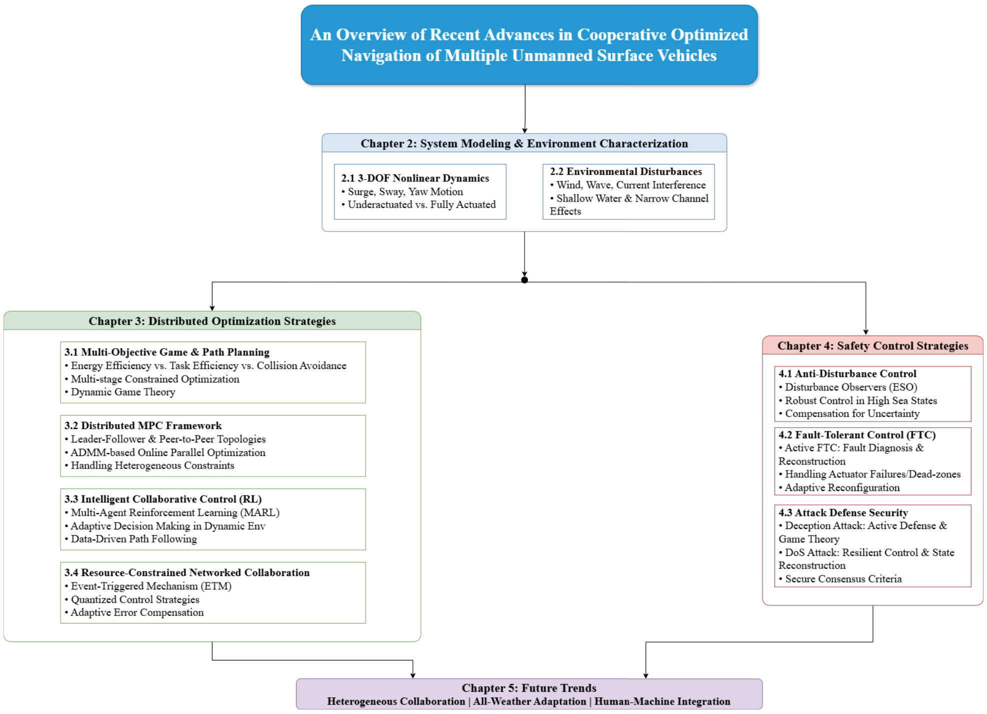
USVs refer to autonomous or remotely operated craft capable of executing diverse missions on the sea surface or inland waters. They have attracted extensive attention and achieved substantial development in recent years[1]. Based on actuator configurations, USVs are categorized into fully-driven and un-actuated types. Equipped with redundant propulsion systems such as main, side, or azimuth thrusters, fully-driven USVs independently decouple control over surge, sway, and yaw motions. By achieving this decoupling, these USVs execute high-precision tasks, including low-speed berthing and precise positioning. In contrast, the vast majority of conventional transport USVs and unmanned craft fall under the un-actuated category. Constrained by second-order unactuated constraints, they typically rely solely on stern main propellers and rudders, leaving the sway dynamics un-actuated. Therefore, their control design must fully leverage the nonlinear coupling between surge velocity and yaw motions[2]. Currently, single-USV autonomous navigation technology has matured, while multi-USV formation technology is rapidly emerging. Cooperative control principles can integrate multiple USVs into a unified entity, where spatial redundancy significantly enhances system fault tolerance. This approach fundamentally utilizes the Laplacian matrix from algebraic graph theory to characterize how communication topology constrains individual dynamics, as expressed by:

$$e_{i1} = \sum_{j=1}^{N} a_{ij}\left(\eta_i - \eta_j\right) = \sum_{j=N+1}^{M} a_{ij}\left(\eta_i - \eta_{jd}\right) \tag{1}$$

where η_i and η_j represent the state vectors of the i-th follower USV and its neighbor j, respectively. The term a_{ij} denotes the adjacency weights in the graph derived from the corresponding Laplacian matrix, and η_{jd} indicates the leader's state. This equation demonstrates that individual USVs are no longer solely driven by their own dynamics. Instead, they are coupled within the formation network through the summation term. Consequently, the system transitions from independent individual control to collective cooperative control[3]. Research further demonstrates the advantages of multi-USV formations over single USVs. Specifically, they exhibit superior operational efficiency and mission success rates when executing complex tasks, such as wide-area search, ocean sampling, and towing[4]. Collaborative control for multiple USVs focuses on ensuring consistent consensus on the states of individual entities within the cluster. In contrast, path planning aims to calculate an evolutionary trajectory for the entire formation. This trajectory must be carefully designed to balance time optimization, energy reduction, and enhanced safety[5].

1.2 Logical Framework

Figure1: Logical Architecture Diagram of This Overview



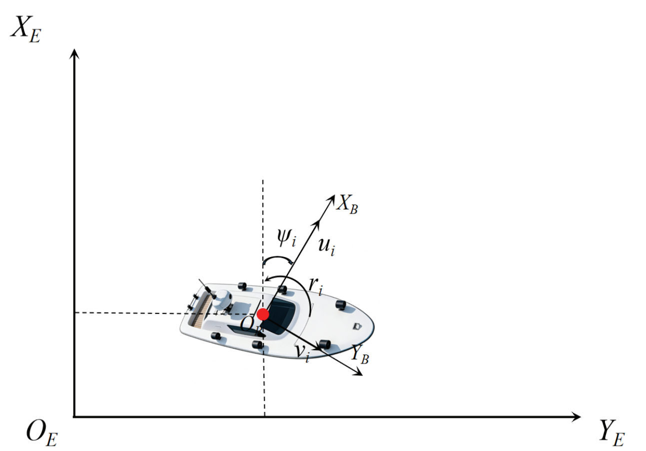
Against this backdrop and challenges, this paper provides a systematic review of autonomous cooperative navigation strategies for multiple USVs. Section 2 first analyzes the nonlinear dynamic models of USVs and the characteristics of oceanic environmental disturbances; Section 3 explores distributed optimization strategies, covering path planning, model predictive control, and reinforcement learning-based intelligent coordination methods, while introducing networked coordination mechanisms under resource constraints; Section 4 focuses on safe navigation strategies, detailing anti-interference techniques, fault-tolerant control, and active defense technologies against malicious cyberattacks. Finally, this paper concludes with a summary and outlook on future development directions in this field.

2. Modeling of Multi-USV Systems and Environmental Disturbance Characteristics

2.1 3-DOF Nonlinear Model of USVs

The mathematical model of ship motion forms the foundation for achieving autonomous cooperative control and optimized navigation, with its precision directly impacting the effectiveness of control strategies. Considering a cooperative formation system composed of N USVs, define the set $V = \{1,2,\ldots,N\}$ to represent the individual ships within the formation. For the i-th USV ($i \in V$) in the formation, we typically focus on its three degrees of freedom (DOF) in the horizontal plane: surge, sway, and yaw motions. To accurately describe its motion state, two coordinate systems are defined: the Earth-fixed frame ($\{E\}$) and the Body-fixed frame ($\{B\}$).

Figure2: Schematic of the Earth-fixed frame and Body-fixed frame for a watercraft



In this figure, the global Earth-fixed frame is denoted by the axes X_E and Y_E, and the local body-fixed frame attached to the USV is represented by the axes X_B and Y_B. The variable ψ_i represents the heading angle of the i-th USV. The symbols u_i, v_i, and r_i explicitly indicate the surge velocity, sway velocity, and yaw angular velocity of the i-th USV within its body-fixed frame, respectively.

The position and heading vector of the USV i in the Earth-fixed frame $\{E\}$ are defined as $\eta_i = [x_i, y_i, \psi_i]^T \in \mathbb{R}^3$. The linear velocity and angular velocity vectors in the Body-fixed frame $\{B\}$ are defined as $v_i = [u_i, v_i, r_i]^T \in \mathbb{R}^3$, where u_i, v_i, r_i respectively represent the surge velocity, sway velocity, and yaw angular velocity. Based on Fossen's theory of ship motion[6,7] and the cooperative control framework mentioned by Peng et al.[8], the nonlinear kinematic and dynamic equations for the nth USV i can be described as:

$$\begin{cases} \dot{\eta}_i = R(\psi_i)v_i \\ M_i\dot{v}_i + C_i(v_i)v_i + D_i(v_i)v_i + g_i(\eta_i) = \tau_i + \tau_{wi} \end{cases} \quad i = 1,\ldots,N \tag{2}$$

where $R(\psi_i) \in \mathbb{R}^{3\times3}$ is the rotation matrix mapping velocities from the body coordinate system to the fixed coordinate system, satisfying the following geometric property: $SO(3)$ Geometric properties:

$$R(\psi_i) = \begin{bmatrix} \cos\psi_i & -\sin\psi_i & 0 \\ \sin\psi_i & \cos\psi_i & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{3}$$

The physical significance and structural characteristics of the matrices in the dynamic equations are as follows: M_i is the inertia matrix incorporating rigid body mass and added mass, as expressed by:

$$M_i = \begin{bmatrix} m_{i11} & 0 & 0 \\ 0 & m_{i22} & m_{i23} \\ 0 & m_{i32} & m_{i33} \end{bmatrix} \tag{4}$$

where m_{i11} represents the mass in the longitudinal direction, m_{i22} represents the mass in the transverse direction,m_{i33} denotes the moment of inertia, and $m_{i23} = m_{i32}$ reflects the coupling effect between transverse and heave motions; $C_i(v_i)$ is the Coriolis and centripetal force matrix, describing the nonlinear forces generated in the rotating coordinate system, as shown in equation:

$$C_i(v_i) = \begin{bmatrix} 0 & 0 & -m_{i22}v_i - m_{i23}r_i \\ 0 & 0 & m_{i11}u_i \\ m_{i22}v_i + m_{i23}r_i & -m_{i11}u_i & 0 \end{bmatrix} \tag{5}$$

$D_i(v_i)$ is the fluid damping matrix, primarily comprising linear and nonlinear damping terms, as shown in equation:

$$D_i(v_i) = \begin{bmatrix} d_{i11}(v_i) & 0 & 0 \\ 0 & d_{i22}(v_i) & d_{i23}(v_i) \\ 0 & d_{i32}(v_i) & d_{i33}(v_i) \end{bmatrix} \tag{6}$$

where $d_{ijk}(v_i)$ represents the velocity-dependent nonlinear hydrodynamic damping coefficient. Additionally, $g_i(\eta_i)$ denotes the restoring torque generated by buoyancy and gravity; $\tau_i = [\tau_{ui}, \tau_{vi}, \tau_{ri}]^T$ is the control input vector for the i-th USV, comprising longitudinal thrust, lateral thrust, and yaw moment from the propeller; and $\tau_{wi} = [w_{ui}, w_{vi}, w_{ri}]^T$ $\boldsymbol{\tau_{wi}} = [\boldsymbol{w_{ui}}, \boldsymbol{w_{vi}}, \boldsymbol{w_{ri}}]^{\boldsymbol{T}}$ represents the vector of uncertain external disturbances from wind, waves, and currents.

Based on the different configurations of the control input vector τ_i, the model can be further categorized into fully-driven and un-actuated types:

Fully-driven USVs: Fully-driven USVs are equipped with main propulsion and side-push device, featuring independent control inputs across all three degrees of freedom: surge, sway, and yaw motions. Its control vector is expressed as $\tau_i = [\tau_{ui}, \tau_{vi}, \tau_{ri}]^T \in \mathbb{R}^3$, where $\tau_{ui}, \tau_{vi}, \tau_{ri}$ represent longitudinal thrust, lateral thrust, and yaw moment, respectively, all of which are non-zero. Consequently, this USV type satisfies the integrity constraint, exhibits excellent maneuverability, and can achieve precise point-holding and accurate tracking of arbitrary curves.

Un-actuated USVs: Most transport USVs are un-actuated, typically equipped only with a stern propeller and rudder. They have fewer independent control inputs than degrees of freedom, with a typical configuration lacking independent lateral thrust. Their control vector form is $\tau_i = [\tau_{ui}, 0, \tau_{ri}]^T$, where the lateral control force is $\tau_{vi} = 0$. Constrained by second-order unactuated constraints, direct lateral translation is restricted. Lateral position changes are achieved through the coupling of longitudinal and yaw motions, which increases the complexity of controller design compared to fully-driven systems.

2.2 Ocean Physical Environment Disturbance Model

2.2.1 Disturbance Model of Wind, Waves, and Currents

When operating in actual sea conditions, a USV's motion state inevitably undergoes complex influences from the marine environment. The total environmental disturbance acting on the hull, τ_{env}, can be regarded as the nonlinear superposition of wind disturbance force τ_{wind}, wave disturbance force τ_{wave}, and current disturbance force $\tau_{current}$. In the body-fixed frame, this superposition model can be expressed as[6,7]:

$$\tau_{env} = \tau_{wind} + \tau_{wave} + \tau_{current} \tag{7}$$

where $\tau_{env} \in \mathbb{R}^3$ denotes the environmental disturbance vector comprising longitudinal heave forces, transverse heave forces, and bow-stern pitching moments. The mathematical modeling of these three disturbance forces is described below.

Wind Disturbance Model: The primary effect of wind on USVs manifests as aerodynamic forces acting on the hull above the waterline and superstructures. Typically, a composite model combining mean wind speed and gust wind speed is employed to characterize the wind field. The wind disturbance forces and moments acting on the hull are described by the Isherwood empirical formula as[6,7]:

$$\tau_{wind} = \frac{1}{2}\rho_a V_{rw}^2 \begin{bmatrix} A_T C_X(\gamma_{rw}) \\ A_L C_Y(\gamma_{rw}) \\ A_L L_{oa} C_N(\gamma_{rw}) \end{bmatrix} \tag{8}$$

In the equation, ρ_a represents air density; V_{rw} denotes relative wind speed, i.e., the resultant magnitude of the true wind speed vector and the USV's motion velocity vector; A_T and A_L represent the wind-exposed areas of the hull above the waterline in the transverse and longitudinal directions, respectively; L_{oa} denotes the USV's overall length. The coefficients $C_X(\gamma_{rw})$、$C_Y(\gamma_{rw})$ and $C_N(\gamma_{rw})$ in the vector denote the wind load coefficients for longitudinal force, lateral force, and bow-stern moment, respectively. These are functions of the relative wind angle γ_{rw} , and their specific values are typically determined through wind tunnel testing or empirical charts.

Wave Disturbance Model: Wave disturbance impacts USV control systems primarily through high-frequency first-order wave forces and low-frequency second-order wave forces. Since first-order wave forces typically exceed the propeller's response bandwidth, control systems generally compensate for slow drift motion caused by second-order wave forces. Based on long-crested wave theory, ocean waves are described as the superposition of multiple cosine waves at different frequencies. The Pierson-Moskowitz spectrum characterizes wave energy distribution, and the second-order wave drift force can be approximated as[6,7]:

$$\tau_{wave}(t) = \sum_{i=1}^{N}\sum_{j=1}^{N} \sqrt{2S(\omega_i)\Delta\omega}\sqrt{2S(\omega_j)\Delta\omega} \ \times \ \overline{T}_{drift}(\omega_i,\omega_j)\cos\left[(\omega_i-\omega_j)t+(\phi_i-\phi_j)\right] \tag{9}$$

where $S(\omega_i)$ and $S(\omega_j)$ represent the wave spectral density function values at corresponding frequencies ω_i, ω_j; $\Delta\omega$ denotes the frequency sampling interval; ϕ_i, ϕ_j is a random phase angle uniformly distributed within the range $[0, 2\pi]$; $\overline{T}_{drift}(\omega_i,\omega_j)$ is termed the second-order transfer function, reflecting the efficiency of wave energy conversion into low-frequency drift forces, which is closely related to wave frequency and hull geometry.

Current Disturbance Model: Currents primarily exert viscous drag and lift forces on the underwater hull section. In engineering practice, currents are typically assumed steady-state over short durations and incorporated into the dynamic model via the relative velocity method. The disturbance forces and moments generated by currents are formally analogous to wind disturbances, adhering to fluid dynamics principles. Their mathematical expressions are given by[6,7]:

$$\tau_{current} = \frac{1}{2}\rho_w V_{rc}^2 \begin{bmatrix} L_{pp} d C_{Xc}(\gamma_{rc}) \\ L_{pp} d C_{Yc}(\gamma_{rc}) \\ L_{pp}^2 d C_{Nc}(\gamma_{rc}) \end{bmatrix} \tag{10}$$

where ρ_w denotes seawater density; V_{rc} and γ_{rc} represent the magnitude and relative direction angle of the hull's velocity relative to the current, respectively; L_{pp} is the ship's length between perpendiculars;d represents the ship's draft. $C_{Xc}(\gamma_{rc})$、$C_{Yc}(\gamma_{rc})$ and $C_{Nc}(\gamma_{rc})$ are the longitudinal, transverse, and moment flow load coefficients of the underwater hull at different relative direction angles, respectively. These coefficients collectively reflect the influence of the hull's underwater shape on hydrodynamic performance.

2.2.2 Nonlinear Fluid Perturbation Model for Complex Waters and Shallow Water Effects

In ports, inland waterways, or nearshore zones, fluid environments differ from those in deep waters. For autonomous inland vessels, Zhang et al. defined the physical constraints of complex water areas as the superposition of shallow water and bank effects. Restricted water depths and channel boundaries limit maneuvering space and alter fluid dynamic transmission mechanisms. Macroscopically, these constraints cause a nonlinear increase in propulsion resistance and modify energy consumption characteristics. Microscopically, they induce pressure redistribution in the flow field around the hull[9].

To precisely quantify shallow-water physical effects at the mathematical model level, Yang and El Moctar proposed a modified shallow-water maneuvering motion model. Addressing prediction distortions in confined waters under traditional Abkowitz-type equations, this model revises the assumption that the damping matrix $D(v)$ depends solely on hull velocity. Instead, it reconstructs it as a state-function matrix $D(v, h/T)$ dependent on the water depth-to-draft ratio[10]. The complete hydrodynamic loads acting on the system comprise longitudinal force X, lateral force Y, and yaw moment N. All require correction factors applied to their deep-water reference values:

$$\begin{cases} X_{shallow}(u,v,r,\delta,h/T) = X_{deep}(u,v,r,\delta) \times f_X(h/T) \\ Y_{shallow}(u,v,r,\delta,h/T) = Y_{deep}(u,v,r,\delta) \times f_Y(h/T) \\ N_{shallow}(u,v,r,\delta,h/T) = N_{deep}(u,v,r,\delta) \times f_N(h/T) \end{cases} \tag{11}$$

where u, v, r represent the ship's surge velocity, sway velocity, and yaw angular velocity, respectively; δ denotes the rudder angle input; X_{deep}, Y_{deep}, N_{deep} represents the reference hydrodynamic forces and moments at infinite water depth. h denotes water depth, T represents the ship's draft, and h/T is the water depth-to-draft ratio, a key parameter characterizing the strength of shallow water effects. $f(h/T)$ constitutes the core depth correction function, mathematically formulated as a power function based on regression analysis. This describes the physical phenomenon where the ship's added mass, damping coefficient, and fluid resistance increase sharply and nonlinearly as h/T decreases:

$$f(h/T) = 1 + \sum_{i=1}^{n} \alpha_{\mathrm{i}} \left(\frac{T}{h}\right)^{\beta_i} \tag{12}$$

where α_i and β_i represent shallow-water hydrodynamic coefficients. By reconstructing static dynamic parameters into state-dependent variables that evolve dynamically with water depth, this model accurately captures the abrupt changes in fluid resistance caused by the shallow-water squat effect, providing a physically constrained system model for collaborative navigation optimization.

Building upon the modified hull dynamics model, Liu et al. developed an analytical wave-current interaction model based on homotopy analysis. This model is designed to address the strong nonlinear coupling interference between waves and currents in finite water depths[11]. Unlike the linear superposition principle, this model accounts for the modulation effects of finite water depth d on wave-current fields. Assuming the fluid is inviscid, incompressible, and irrotational, the flow field is described by the velocity potential $\phi(x, z, t)$ satisfying the Laplace equation $\nabla^2\phi = 0$. The nonlinear characteristics are primarily manifested in the kinematic and dynamic boundary conditions at the free surface $\zeta(x, t)$:

$$\frac{\partial \zeta}{\partial t} + \frac{\partial \phi}{\partial x}\frac{\partial \zeta}{\partial x} - \frac{\partial \phi}{\partial z} = 0, \quad z = \zeta(x, t) \tag{13}$$

$$\frac{\partial \phi}{\partial t} + \frac{1}{2}\left[\left(\frac{\partial \phi}{\partial x}\right)^2 + \left(\frac{\partial \phi}{\partial z}\right)^2\right] + g_0\zeta = \frac{1}{2}U^2, \quad z = \zeta(x, t) \tag{14}$$

In the above system of equations, $\zeta(x, t)$ represents wave height, g_0 denotes gravitational acceleration, and U signifies the background uniform flow velocity. By employing homotopy analysis to solve this system, an analytical solution is derived. This solution explicitly incorporates Doppler shift effects and waveform modulation. This model confirms that as water depth d decreases, wave-current coupling significantly intensifies, causing substantial fluctuations in the second-order wave drift force. If this nonlinear environmental perturbation induced by shallow water is neglected in the algorithm, it leads to observer estimation errors. Consequently, the positioning accuracy for USVs in restricted waters is reduced.

Equations (13) and (14) define the free-surface boundary conditions for nonlinear wave-current interactions. The solution of these equations yields the velocity potential and surface elevation, which influence the USV's dynamic mathematical model. The resulting wave-current flow field alters the hydrodynamic pressure distribution on the hull, modifying the added mass and damping coefficients in the maneuvering model[10]. The generated nonlinear wave drift forces and increased resistance are incorporated into the USV's 3-DOF dynamic equations as the external environmental disturbance vector τ_{env}[9]. These formulations establish the theoretical foundation for calculating external disturbances and correcting hydrodynamic coefficients.

3. Distributed Optimization Strategy for Multi-USVs

3.1 Multi-Objective Game Theory and Optimized Path Planning

3.1.1 Multi-Objective Trade-off and Decision Mechanism for Mission Efficiency, Energy Consumption, and Collision Avoidance

In collaborative missions involving multiple USVs, mission efficiency, energy consumption, and navigational safety exhibit strong coupling and inherent conflicts. Establishing an efficient multi-objective tradeoff and decision-making mechanism is critical for achieving autonomous operation of USV clusters.

Regarding trajectory planning in highly dynamic game scenarios, Xu et al. studied the "approach-avoidance" differential game for multi-un-actuated autonomous surface vehicles. A control obstacle function was employed to construct a strict safety constraint boundary. Concurrently, geometric methods were used to compute optimal capture points. This approach ensures defenders achieve absolutely collision-free interception strategies at the planning level[12]. Hard constraints based on geometric methods often yield overly conservative planning results. It becomes difficult to find feasible solutions in dynamically congested environments. To address multi-objective conflicts in complex environments during the planning phase, Xiao et al. integrated the physical cost of the "velocity obstacle method" into a deep reinforcement learning framework. Unmanned surface vehicles can thus effectively balance and avoid high-risk areas while maximizing target approach efficiency during autonomous path planning[13]. Game-theoretic planning strategies are transitioning from pursuing mathematically optimal Nash equilibrium toward engineering practicality, balancing real-time obstacle avoidance with long-endurance energy efficiency. Achieving rapid convergence in unstructured environments remains challenging.

To establish trade-off mechanisms for formation configuration and mission efficiency, Shi and Ye proposed a distributed optimization method based on regularized games[14]. Their method utilizes the Nash equilibrium point as the optimal decision state. This state balances individual energy consumption minimization and fleet formation maintenance. Collaborative configuration planning under distributed architectures is thus achieved. Path discontinuity in marine sampling tasks causes significant energy consumption issues. MahmoudZadeh et al. developed a "non-discontinuous" path planning system based on B-spline data frames[15]. This system constructs a B-spline-based data structure for intelligent sampling of candidate task points. USVs can complete sampling operations without full shutdown during navigation. Generating smooth trajectories significantly reduces unnecessary energy consumption from frequent starts and stops. Multidimensional objectives at the planning layer have inherent conflicts. Yin et al. proposed a multistage constrained multi-objective optimization strategy to precisely address these conflicts[16]. Collision avoidance constraints and collaborative efficiency objectives are decoupled in phases. Ultimately, a set of Pareto-optimal path solutions is obtained. These solutions flexibly adapt to different mission preferences.

3.1.2 Multi-stage Constrained Optimization Planning Algorithms in Dynamic Environments

In dynamic and complex marine environments, a single planning strategy struggles to simultaneously satisfy multi-dimensional constraints such as collision avoidance safety, mission sequencing, and formation coordination. Multi-stage, hierarchical optimization algorithms emerge as an effective approach to address such challenges. For fundamental obstacle-avoidance path generation, Wang et al. integrated the International Regulations for Preventing Collisions at Sea directly into the planning layer[17]. Their method enhances genetic algorithm operators and combines them with the Analytic Hierarchy Process. Navigation-compliant cooperative trajectory planning is achieved. For complex tasks across heterogeneous domains, Wu et al. enhanced the particle swarm optimization algorithm to construct a phased planning model[18]. This model decouples the task into independent "search" and "tracking" phases. Trajectory planning complexity under multiple constraints is effectively reduced.

For spatio-temporal allocation planning across large-scale multi-objective points, hierarchical architectures demonstrate significant advantages. Yao et al. proposed a two-layer planning framework based on self-organizing maps and spectral clustering[19]. This framework separates high-level target assignment from low-level path generation. An energy cost function is utilized to guide planning. The approach adapts to cluttered environments. Such hierarchical decoupling strategies significantly reduce computational complexity in high-dimensional state spaces. These strategies often come at the cost of global optimality. Systems lacking frequent information feedback between upper and lower-layer planners are prone to deadlock states in dense obstacle environments. Luo and Su designed a multi-stage strategy for area coverage tasks[20]. This strategy integrates lock-on scanning with an improved ant colony algorithm. A greedy mechanism and a reconstructed heuristic function are utilized. Task sequence planning conflicts under complex spatiotemporal constraints are resolved.

Under complex marine constraints, the aforementioned heuristic algorithms yield high-quality feasible or sub-optimal solutions rather than absolute global optima. Compared to exact optimization algorithms that incur exponential computational loads to seek global optimal paths, heuristic solutions provide high computational efficiency and real-time collision avoidance capabilities in dynamic environments. In multi-objective optimization formulations, objective weights are allocated via mathematical models or task priorities. These weights are established using the Analytic Hierarchy Process (AHP)[17], comprehensive cost assessment functions[20], or dynamic objective shifts across different mission phases[18].

3.2 Distributed Model Predictive Control Framework

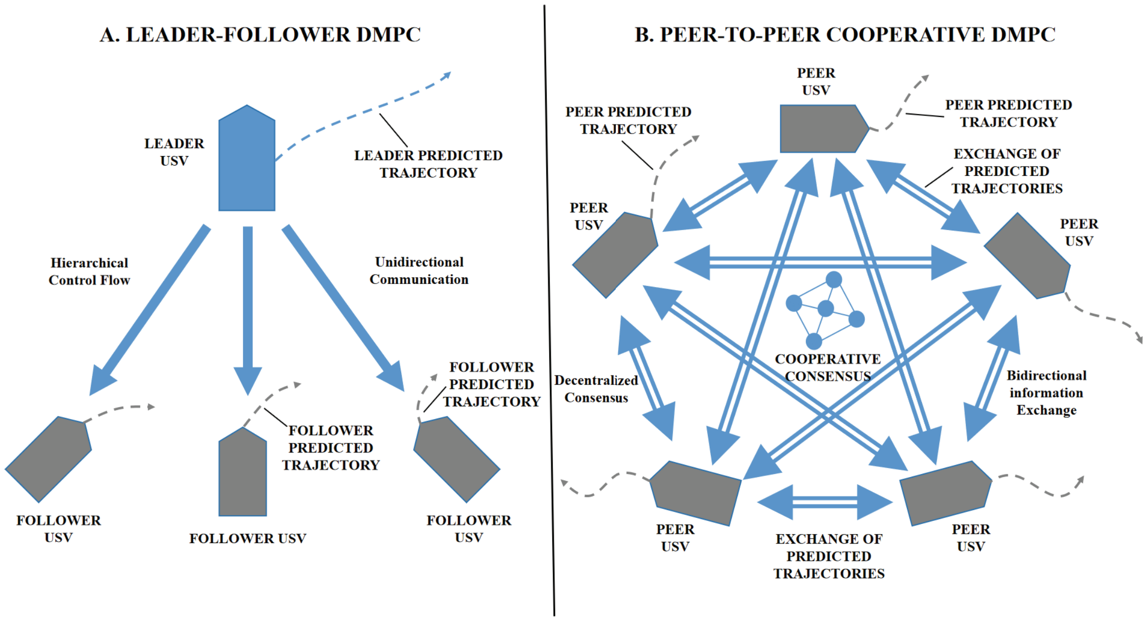
3.2.1 DMPC Architecture in Leader-Follower and Peer-to-Peer Topologies

Within the Distributed Model Predictive Control (DMPC) framework, the communication topology dictates information flow directions. This topology determines the construction of collaborative constraints during the prediction time domain. Existing collaborative architectures primarily fall into two categories based on task coupling. These categories comprise hierarchical leader-follower models and decentralized peer-to-peer cooperative models.

Within distributed Model Predictive Control (MPC) systems, the communication topology directly shapes the construction of state constraints during prediction. The leader-follower architecture is commonly employed for standard trajectory tracking. This architecture provides strong computational decoupling. Wu et al. developed a nonlinear MPC framework based on a virtual leader strategy[21]. This framework demonstrates robustness against time-varying disturbances like tidal currents. Long formations are prone to "serial stability" issues. Chen et al. proposed a serial iterative architecture to address these issues[22]. This architecture optimizes relative errors between adjacent vessels. Error propagation amplification along the formation is effectively suppressed. Such hierarchical architectures greatly simplify stability analysis. These architectures carry a high risk of single-point failure. Interruption of communication with the lead vessel puts the entire formation at risk of paralysis.

Peer-to-peer topologies are employed to establish bidirectional consensus on neighbor node states, rendering them suitable for accomplishing tightly coupled tasks. To address multi-objective encirclement, Zhu et al. implemented a ring-enveloping rule based on neighbor information exchange during computation. By utilizing distributed coordination, this method overcomes task interruptions caused by single-point failures[23]. For physically coupled systems like marine towing, Du et al. noted that mere position tracking cannot guarantee dynamic stability and struggles against nonlinear disturbances from connector constraints. Consequently, they proposed a fully connected dynamic coordination control method to solve real-time consensus problems for towing force and motion attitude[24]. Although fully connected peer-to-peer topologies enhance robustness, their communication load grows exponentially with fleet size, which limits their application in large-scale clusters.

Figure3: Comparison of typical communication topologies in distributed cooperative control



In this figure, the left side illustrates the leader-follower topology, and the right side shows the peer-to-peer topology. The blue boat icon designates the Leader USV, while the gray boat icons represent the Follower USVs. And the dashed line represents the predicted trajectory of the Leader USV. The connecting lines and arrows indicate the communication links and the direction of information flow among the USVs within the network.

3.2.2 Online Parallel Optimization Algorithm Based on the Alternating Direction Method of Multipliers

To address the high-dimensional solution challenges in centralized optimization for large-scale multi-USV systems, optimization algorithms based on the Alternating Direction Method of Multipliers (ADMM) are employed to decouple global constraint optimization problems into parallelizable local subproblems. This approach enables the efficient solution of distributed model predictive control problems, standing as one of the primary operator splitting techniques for such applications.

For strongly physically coupled marine towing tasks, Du et al. established a distributed model predictive control framework based on augmented Lagrangian functions. This framework decomposes complex coordination problems into three independent subproblems: force optimization for the towed vessel, trajectory tracking for the tugboat, and Lagrangian multiplier updates for consistency constraints. By abandoning traditional master-slave control logic, each cooperative unit exchanges multipliers and boundary states to achieve rapid dynamic convergence. Consequently, computational complexity is reduced while strictly satisfying the International Regulations for Preventing Collisions at Sea (COLREGs) collision avoidance criteria[25].

Traditional synchronous ADMM requires all nodes to complete their computations before proceeding to the next iteration. Because the slowest node becomes the common bottleneck, this approach introduces control delays in heterogeneous or communication-constrained marine networks. To address this limitation, Tran et al. introduced an asynchronous nonlinear ADMM algorithm, which allows vessels to perform local control law computations within the current iteration cycle using only updates from their local neighbors. To mitigate prediction errors arising from asynchronous information exchange, the concept of "intent consensus" is introduced for correction. Experiments validated that this parallel architecture reduces communication wait times for vessel groups under complex inland waterway traffic conditions, enhancing the robustness and real-time performance of coordinated collision avoidance systems in suboptimal network environments[26]. Although the ADMM algorithm resolves computational decoupling, its iteration count remains highly sensitive to communication delays. Future research will focus on reducing iteration interactions to accommodate low-bandwidth marine environments.

In multi-vessel coordination, reducing ADMM iterations decreases computational and communication loads but induces incomplete consensus, yielding sub-optimal solutions that violate collision constraints[25]. The iteration dynamically terminates when primal and dual residuals meet safety tolerances, or is truncated by a maximum cap to guarantee real-time computing[26]. Convergence iterations depend on augmented Lagrangian penalty parameters[24], physical constraint complexity, and communication synchronicity. Adopting an asynchronous ADMM framework eliminates slower vessels' waiting times, accelerating real-time execution despite variations in total convergence steps[26].

3.3 Learning-Based Intelligent Cooperative Control

The application of learning-based technologies in this section differs from Section 3.1. Section 3.1 employs machine learning for kinematic-level path planning and multi-objective games, establishing spatial routing and logic-based conflict resolution. Section 3.3 addresses dynamic uncertainties and physical model limitations. These learning technologies manage strong nonlinear fluid disturbances, unmodeled USV dynamics and dynamically changing cluster sizes during execution.

3.3.1 Application of Reinforcement Learning in Collaborative Decision-Making

Due to the limitations of traditional model-based control methods in handling strong nonlinear fluid disturbances and dynamically changing environments, reinforcement learning has emerged as a core technological paradigm for achieving intelligent collaborative decision-making in unmanned surface vehicles. This paradigm relies on its powerful feature extraction and trial-and-error learning capabilities.

The primary challenges in this field currently lie in overcoming scalability issues for large-scale multi-agent reinforcement learning and ensuring training convergence. Existing centralized training methods typically require predefined fixed environmental input dimensions, which makes them ill-suited for scenarios where agent numbers dynamically change across mission phases. To address this challenge, Wang et al. proposed integrating bidirectional long short-term memory

(LSTM) networks into the scalable Multi-Agent Deep Deterministic Policy Gradient (MADDPG) resilience framework[27]. This framework enables multi-UUV systems to dynamically adjust cluster size by flexibly adding or removing nodes during cooperative intrusion missions, allowing the system to rapidly adapt to evolving engagement environments without retraining the existing model.

To address sparse rewards and training oscillations common in coordination, Wang et al. proposed a deep reinforcement learning strategy with a deceleration mechanism. By modifying the reward function using an artificial potential field approach, they avoided ineffective exploration during the initial phase, and an adaptive deceleration strategy ensured formation stability during high-speed movement[28]. Despite performing well in simulation environments, these algorithms suffer from extremely slow training convergence in real sea conditions due to sparse rewards, and the "trial-and-error" mechanism incurs high trial costs in actual physical systems.

Real maritime environments present challenges such as communication limitations and partial observability, meaning local and global perception cannot fully meet the requirements of collaborative decision-making. To address scenarios with missing velocity information or unknown dynamic parameters, Xiao et al. proposed a value decomposition-based reinforcement learning approach[29]. This method reconstructs missing states using a trace-free Kalman filter observer and employs a hybrid network architecture to decompose global rewards into individual components, thereby achieving robust formation control under incomplete information. To address information redundancy in large-scale dynamic games, Xue et al. established a differential game-based adversarial model and proposed a multi-agent reinforcement learning algorithm integrating multi-head self-attention mechanisms. By enabling agents to adaptively focus on critical state information, this mechanism filters key neighboring nodes and core environmental features. Consequently, agents can accurately discern adversary intentions from massive observations, enhancing the collaborative efficiency and success rate of capture strategies[30].

Reinforcement learning demonstrates adaptability in low-level motion control and anti-interference. Qu et al. designed a path-following control scheme based on deep reinforcement learning[31]. They overcame control challenges for un-actuated unmanned surface vehicles under model uncertainty. For complex scenarios with limited inputs and unknown dynamics, Wang et al. combined the Actor-Critic architecture with finite-time control theory. They achieved high-precision trajectory tracking for USVs[32]. To enhance data utilization efficiency, Peng et al. proposed a model-based deep reinforcement learning approach. They constructed predictive models through data-driven methods. Efficient path following and trajectory tracking are achieved. Reliance on physical models is reduced[33]. From an anti-interference perspective, Liu et al. integrated reinforcement learning algorithms into communication protocols and underlying dynamic control. The system is endowed with robust disturbance learning capabilities under random wind and wave disturbances. The impact of environmental uncertainty on operational efficiency is mitigated[34].

To overcome the lack of interpretability and excessive reliance on data inherent in purely data-driven approaches, hybrid architectures integrating physical model knowledge with data-driven methods are developed to address uncertainty disturbances. Unmanned surface vehicle systems present widespread model uncertainty and difficulty in satisfying continuous reinforcement conditions. Chen et al. proposed an online adaptive reinforcement learning algorithm based on an identifier-evaluator architecture. They utilized an improved evaluator network adaptive law to relax the constraints on continuous reinforcement conditions. This approach requires only bounded controllability and asymptotic ergodicity. Optimal trajectory tracking over an infinite time domain is achieved[35]. To address the challenge of directly measuring state variables, Yuan et al. designed an output-feedback adaptive optimal control scheme based on a neural network velocity observer. This approach employs neural networks to estimate unobservable states and unknown dynamic parameters. A disturbance observer is utilized to counteract sea state disturbances. Desired trajectory tracking is enabled without full state feedback[36].

To enhance communication and computational efficiency in networked cooperative systems, Xue et al. combined data-driven integral reinforcement learning with dynamic event-driven mechanisms to design a hybrid adaptive dynamic programming method. This approach utilizes augmented error as a discrimination criterion, reducing control law update frequency and network load. Experiments demonstrate that this algorithm reduces the required sample size by nearly 78% compared to static strategies, improving the real-time performance and resource utilization of online learning[37]. To address the dual challenge of safe obstacle avoidance and energy balance in formation navigation, Li et al. proposed an Actor-Critic neural network control method employing a gain-iterative disturbance observer. This iterative mechanism dynamically adjusts gain values to achieve precise estimation of time-varying disturbances. By integrating artificial potential field methods, self-reinforcement learning, and trajectory planning, this research ensures collision-free multi-USV formation while simultaneously achieving dual objectives of optimal control performance and minimal energy consumption[38]. Modern adaptive dynamic programming methods are evolving from single-objective optimization toward holistic architectures. These architectures incorporate state observation, event-triggered, and safety constraints.

3.3.2 Applications of Other Intelligent Learning Methods

Hybrid intelligent methods based on fuzzy logic, neuro-dynamics, and transfer learning are gaining prominence. USV cooperative control faces limitations such as insufficient computational real-time capability, slow convergence with small samples, and model interpretability issues. These approaches address these limitations. Computational speed and environmental adaptability are enhanced.

Model Predictive Control (MPC) presents a substantial computational load during online operations. Lyu et al. proposed a neural dynamics optimization approach. By utilizing the parallel processing capabilities of Recurrent Neural Networks (RNN) to establish a parallel control system architecture, this approach achieves safe collision avoidance under multi-USV state constraints while ensuring control real-time performance[39]. To address parameter uncertainty and communication resource constraints in un-actuated USVs, Qin and Du proposed a finite-time event-triggered control scheme based on minimal learning parameters. By replacing complex neural network approximations with minimal learning parameter techniques, this approach reduces the computational burden. Event-triggered decreases the controller update frequency to actuators. Communication resources are conserved while system stability is maintained[40].

Furthermore, addressing safety hazards from sensor failures and parameter convergence challenges in small-sample environments, Chu and Li proposed a fault-tolerant distributed composite learning method. This approach incorporates prediction errors into the neural network, using them to drive parameter updates and accelerate learning speed[41]. In contrast, addressing obstacle avoidance and velocity unpredictability in formation navigation, Wu and Tong developed a finite-time adaptive fuzzy control framework based on an improved potential function. By designing a fuzzy state observer to reconstruct unmeasured states and incorporating an event-triggered mechanism, they achieved semi-global finite-time collision-free formation tracking for multi-USV systems while significantly reducing communication resource consumption[42].

3.4 Networked Collaboration in Resource-Constrained Environments

3.4.1 Dynamic Event-Triggered Mechanism Under Limited Communication Bandwidth

Due to scarce maritime communication resources, time-triggered communication mechanisms generate excessive redundant data. These mechanisms cannot meet the real-time requirements of multi-USV collaborative operations. Dynamic event-triggered communication provides a flexible alternative. This approach determines data transmission based on internal dynamic variables or time-varying thresholds within the control system. By determining data transmission dynamically, communication frequency is reduced while control performance is maintained.

Hu et al. proposed an adaptive cooperative disturbance rejection control architecture based on internal dynamic variables. In this architecture, dynamic trigger conditions filter out minor disturbances affecting system stability. Propulsion system execution frequency is reduced and unknown sinusoidal disturbances are suppressed. Control increments are decreased[43]. To resolve the conflict between formation tracking accuracy and bandwidth occupancy, Ning et al. proposed a distributed event-triggered mechanism based on time-varying thresholds. This mechanism allows trigger thresholds to adapt to system errors. By employing dual quantization of inputs and states, they achieved accelerated formation tracking for un-actuated unmanned surface vehicles[44].

For quality switching and energy-constrained problems in networked USV systems, Bo et al. proposed an energy-efficient event-triggered $H\infty$ filtering algorithm based on hysteresis quantization. Using an augmented Lyapunov functional, they demonstrated that this mechanism prevents Zeno phenomena. State estimation accuracy is ensured under signal transmission delays and limited bandwidth conditions[45]. Dynamic event-triggered mechanisms have become a key technical approach to resolving communication bottlenecks in networked USV collaboration.

3.4.2 Quantization Control Strategies in Signal Transmission

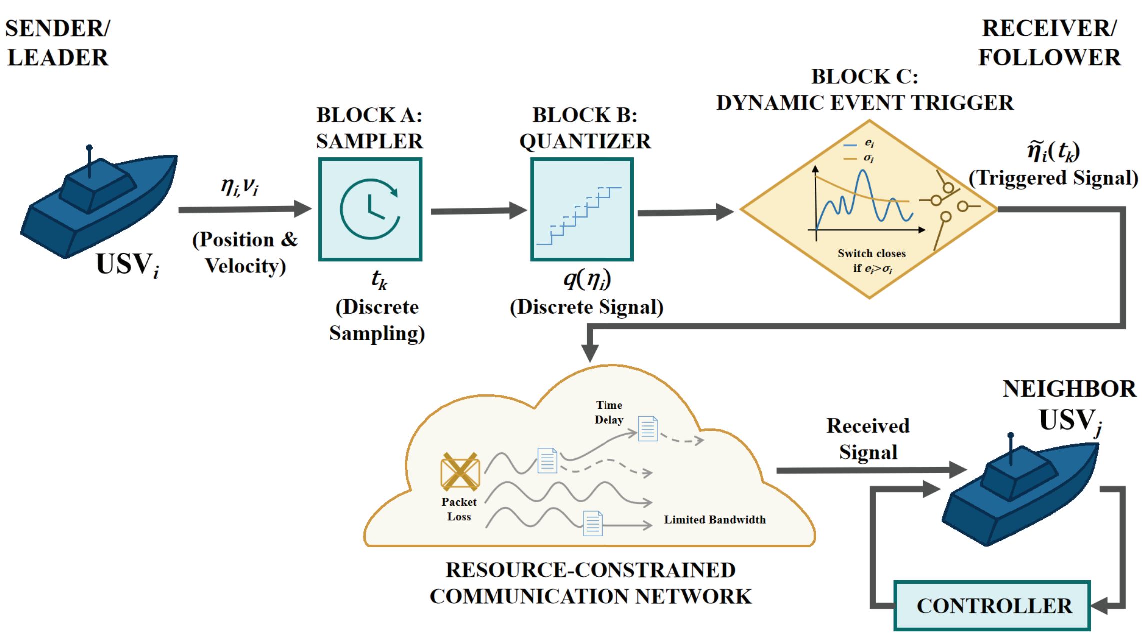
In marine low-bandwidth communication environments, signal quantization strategies compress the size of individual transmission packets. These strategies complement event-triggered mechanisms that reduce communication frequency. The discrete nature introduced by signal quantization, sampling-induced delays, and sector-bounded quantization errors trigger system oscillations or instability. Quantization errors are primarily treated as system uncertainties or external disturbances. Adaptive methods are employed for compensation[46].

To overcome the dual quantization challenges affecting both inputs and states in un-actuated USVs, solutions based on adaptive backstepping methods are proposed. Xu et al. employed parameter tuning techniques to minimize the impact of full-state quantization errors on tracking accuracy. Practical system stability is established[47]. Ning et al. employed neural network observers to reconstruct quantized state information. They introduced the Nussbaum function to address the unknown control direction problem caused by quantization[46].

For networked formation coordination, the nonlinear characteristics introduced by quantization coupled with complex physical constraints increase control difficulty. Wang et al. incorporated uniform quantizers into distributed formation control. This approach achieves maneuver control while ensuring data compression among multiple USVs without collisions or velocity constraints[48]. Under conditions where velocity information is unmeasurable and communication jitter is prevalent, Park and Yoo proposed a neural network output feedback control method based on hysteretic quantizers. By leveraging the hysteretic quantizer's inherent delay and its ability to prevent signal oscillation between quantization levels, this method ensures cooperative tracking capability for multi-USV formations under directed communication topologies. It relies solely on quantized position and heading angle data[49].

Well-designed quantizers and error compensation algorithms enable systems to achieve high control accuracy while reducing communication overhead. Relying solely on robust control algorithms is insufficient for extremely constrained network environments. Future research will focus on the joint design of control and communication systems to dynamically adjust control strategies based on network conditions.

Figure4: Schematic of Event-Triggered and Quantization-Based Cooperative Control for Multiple USVs



In this figure, the boat icons represent the Leader USV and the Neighbor USV, while the cloud icon represents the communication network. The rectangular blocks illustrate the signal flow through the Sampler, Quantizer and Event-Triggered Mechanism. The connecting lines with arrows indicate the direction of signal flow and data transmission between these blocks.

4. Safety Control Strategy for Multi-USVs

4.1 Anti-Disturbance Safety Control Technology

4.1.1 Disturbance Observer Technology and Its Application in Marine Control

In USV control, observer-based estimation and compensation primarily address disturbances from wind-wave-current environments and model uncertainties. Compared with frequency-domain disturbance observers, Gu et al.'s extended state observers unify compensation by merging uncertainties within the USV model and external disturbance factors into a "total disturbance". When external conditions deteriorate, the total disturbance reflects stronger disturbance effects. This provides advantages in addressing ship dynamics with strong nonlinear coupling[50].

Fu and Yu proposed a finite-time extended state observer technique. By incorporating the first derivative of disturbances into the extended state, this technique overcomes the conservative design constraint that prohibits zero disturbance derivatives. Higher tracking accuracy during input saturation is achieved[51]. Wu et al. combined a nonlinear observer with the virtual ship guidance concept. Using only position output, they achieved robust estimation of the velocity of heterogeneous unmanned surface vehicles and composite disturbances. The problems of unmeasurable velocity and large velocity differences in heterogeneous clusters are solved[52].

As cooperative control evolves from centralized to networked systems, observer design prioritizes communication constraints and security considerations. Ma et al. proposed a distributed dual-observer architecture to mitigate transmission errors caused by signal quantization. Formation consistency is ensured under bandwidth limitations[53]. To reduce reliance on physical models, Luo et al. proposed a model-free extended state observer. This approach utilizes only the system's input-output data to establish a hyperlocal model for real-time disturbance estimation. Adaptive obstacle avoidance under uncertainty is achieved[54].

4.1.2 Robust Cooperative Control Methods for Complex Sea Conditions

In marine environments, strong nonlinear environmental disturbances and physical limitations of actuators, such as saturation and dead zones, compromise the robustness of cooperative systems. To address the timeliness limitations of asymptotic convergence, Liu et al. proposed a practical fixed-time stability lemma. This approach resolves disturbance rejection under input saturation. By rendering the formation error convergence time independent of the initial state, system peak phenomena caused by high gains are avoided[55]. To address mechanical deadband nonlinearity, Jiang et al. employed an adaptive preset time-encompassing control algorithm combined with event-triggered quantization. High system communication bandwidth occupancy is mitigated[56].

Strong physical coupling and dynamic heterogeneity among multibody systems introduce additional challenges for robust control. Xia et al. employed a force allocation approach to resolve the force distribution problem between multiple tugboats and towed objects in an unpowered floating towing system. Precise trajectory tracking for strongly coupled unactuated objects is achieved[57]. For Unmanned Surface Vehicle–Unmanned Underwater Vehicle (USV–UUV) heterogeneous surface-subsurface rendezvous tasks, Jia et al. introduced a pipe-based model predictive control framework. By incorporating safety pipe constraints, collisions between heterogeneous entities and external disturbances are accounted for[58]. To address the Unmanned Surface Vehicle–Unmanned Aerial Vehicle (USV–UAV) air-sea cross-domain swarm control problem in disturbed environments, Li et al. designed an improved leader-follower algorithm independent of virtual velocity. By utilizing an event-triggered mechanism, robust coordination under bandwidth constraints is achieved[59]. Robust cooperative control establishes a comprehensive safety defense system integrating spatiotemporal constraints, physical coupling, and communication limitations.

The leader-follower mode simplifies the decoupling of dynamic differences and is widely applied in heterogeneous cooperative systems, including USV–UAV cooperative path following[59]. To overcome the single-point-of-failure vulnerabilities inherent in centralized leaders, fully connected peer-to-peer information exchange architectures are investigated for heterogeneous devices. For intelligent USV–UUV heterogeneous marine systems, Jia et al. proposed a robust distributed cooperative rendezvous control scheme[58]. Within such distributed architectures, heterogeneous vehicles exchange state information through communication networks and implement cooperative protocols in a parallel, peer-to-peer manner.

By eliminating the reliance on a global leader, the feasibility of peer-to-peer topologies in cross-domain heterogeneous cooperation is demonstrated.

4.2 Fault-Tolerant Control

Safety control constitutes a comprehensive framework encompassing strategies to protect systems from external threats, such as environmental disturbances and cyberattacks, and internal anomalies. As a subset of this framework, fault-tolerant control mitigates internal hardware or software failures, including thruster degradation and sensor data loss.

Operating for extended periods in harsh sea conditions, USVs' propulsion systems and steering mechanisms to safety hazards from actuator failures. The approach has shifted from passive fault tolerance to active fault-tolerant control based on fault diagnosis and reconstruction. To address the concurrent constraints of amplitude saturation and rate-of-change limitations, Liu et al. employed a projection law to design an adaptive reconfiguration strategy. By utilizing terminal sliding mode control, this approach enables online identification of single/dual-parameter faults while ensuring finite-time convergence under rate-limited actuators[60].

Formation control requires both individual USV control and integrated coordination of the entire formation's state. Wang and Liu proposed a two-layer distributed approach to address this joint control problem. This approach employs a first-layer finite-time estimator, a second-layer fast integral terminal sliding mode control law, and dynamic event-triggered to achieve formation recovery after faults[61].

To address formation control challenges for un-actuated USVs under multiple constraints and intermittent actuator failures, Li et al. proposed an adaptive fault-tolerant control scheme based on fuzzy logic systems. This method employs fuzzy logic systems to approximate unknown nonlinear dynamics and external time-varying environmental disturbances. By utilizing preset performance control techniques to establish formation tracking error constraints, collision avoidance and communication connectivity between adjacent USVs are ensured at the physical level. By integrating dynamic surface control strategies, this scheme overcomes control challenges caused by intermittent actuator failures. The consistent ultimate boundedness of all signals within the closed-loop system is demonstrated. The safe collaborative capability of multi-USV formations under constrained and fault conditions is enhanced[62].

4.3 Attack-Resilient Security Control Techniques

4.3.1 Active Defense Strategies Against Deception Attacks

The openness of networked control systems introduces vulnerabilities to deception attacks. Attackers modify sensors or control information to cause consistency breakdowns in the system. To address this threat, passive robust control has evolved into active defense strategies combining data compensation and game-theoretic adversarial approaches. From a data compensation perspective, Wu et al. proposed an indirect adaptive neural network control method. This approach treats time-varying gains caused by injected attacks and deception attacks as heterogeneous uncertainties. By converting these uncertainties into a onefold linear parameterized form using a single-parameter learning method, trajectory tracking under attack conditions is resolved[63]. For formation systems subject to output constraints, Jiang et al. established a formation error reconstruction mechanism. Based on this mechanism, they designed an adaptive law to eliminate attack signal bias without requiring an observer from the leader[64].

Due to limited network bandwidth and the random occurrence of attacks, optimizing communication mechanisms is required for defense. To address asynchronous spoofing attacks in sensor-controller and controller-actuator dual channels, Han et al. proposed a security consistency criterion based on loop Lyapunov-Krasovskii functionals and sampled data control strategies. Conservatism is reduced[65]. For systems subject to random deception attacks, Sun et al. proposed a dynamic memory-based event triggered mechanism. By performing historical data fusion calculations and employing different temporal representations, they dynamically adjusted triggering conditions. A balance between reduced overhead and enhanced positioning accuracy is achieved[66].

The introduction of artificial intelligence technologies integrates game-theoretic principles into defense strategies. Wang et al. framed the offensive-defensive dynamics during multi-USV pursuit as a Stackelberg game problem. By employing reinforcement learning algorithms to derive optimal strategies, controllers are enabled to proactively suppress attacks as dominant players in the game[67]. To address unbounded anomalous deception attacks, Zhong et al. proposed a secure consistency control method for switching topologies. This approach isolates targets from attacks by severing damaged communication links. The existence of only one switching rule for a given topology restricts its application under random attacks[68].

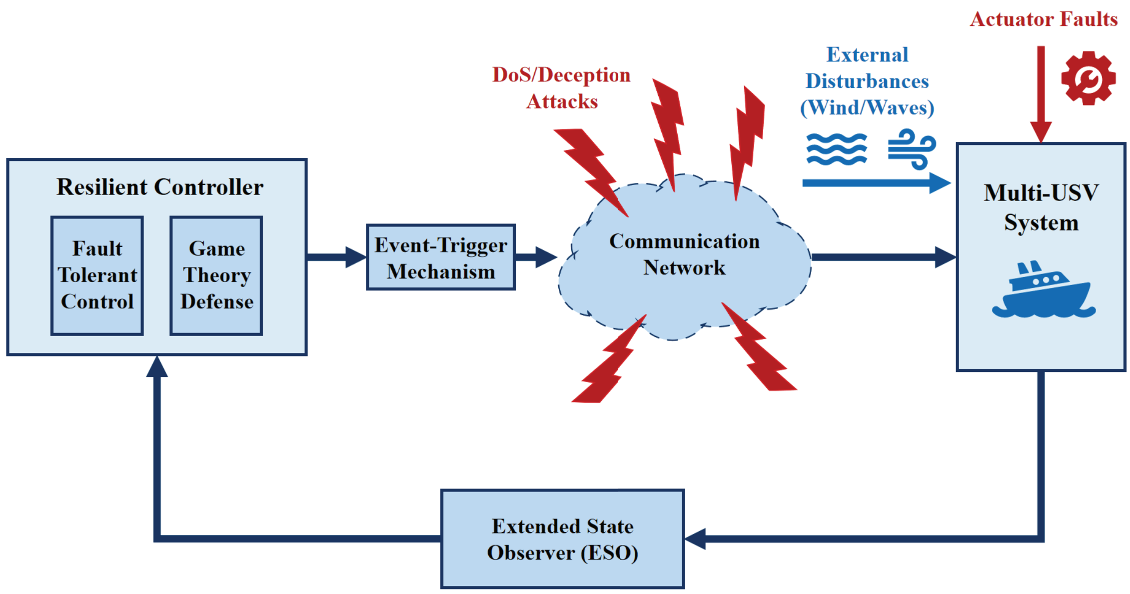
4.3.2 Fault-Tolerant and resilient Control Against Denial-of-Service Attacks

By blocking communication channels, Denial of Service (DoS) attacks cause packet loss or transmission interruptions in networked cooperative control systems. To maintain system stability during communication interruptions, establishing resilience-triggering mechanisms and state reconstruction models serves as a primary defense strategy. For non-periodic DoS attacks, Ma et al. developed a resilience control model based on a time-delay switching system. This model utilizes a dynamic event-triggered mechanism to transmit data during attack intervals while maintaining operation through open-loop prediction during active attack periods. The system is shielded against unknown interference signals[69]. From a fault diagnosis perspective, Li et al. modeled the attacked system as a Markov jump process. They designed an adaptive fault detection filter to predict system anomalies through residual signals under concurrent network resource constraints and attacks. Simultaneous defense and diagnosis are achieved[70].

For multi-USV formations and cooperative operations, elastic control strategies must balance geometric constraints with dynamic performance. Zhang et al. employed a stress matrix approach to solve affine formation control under DoS attacks. This approach requires only the leader's control to achieve formation translation, scaling, and rotation. Its sensitivity to geometric structures restricts its adaptation to non-standard formation changes[71]. For multi-target pursuit missions, Zhang et al. integrated a neural network observer with a dynamic triggering mechanism. Encirclement of escaping targets is achieved under conditions of unobservable velocity states caused by periodic attacks[72].

Cyberattacks coupled with physical-layer failures or constraints introduce additional challenges. For conditions where intermittent actuator failures coexist with DoS attacks, Wu et al. proposed a collision-free distributed adaptive resilient control scheme. This approach employs fuzzy logic to approximate unmodeled dynamics. By utilizing an artificial potential field method, formation safety boundaries are established. The fuzzy approximation process increases the computational load[73]. To address attack-induced velocity measurement loss, Feng et al. constructed a disturbance-robust nonlinear model predictive control framework. By integrating a nonlinear extended state observer, missing signals are compensated in real time. Tracking accuracy is ensured. The high computational demands of the online optimization process restrict the application of this framework on miniaturized unmanned surface vehicle platforms[74].

Figure5: Architecture of the Networked Safety Control System for Multi-USV Networks



In the figure, rectangular blocks denote the core control modules, including the Resilient Controller, Event-Triggered Mechanism, and Extended State Observer. The cloud icon identifies the communication network, with red lightning symbols representing security threats such as cyberattacks. Within the multi-USV system, red and blue arrows signify actuator faults and external environmental disturbances, such as wind and waves, respectively. Connecting arrows indicate the direction of signal flow and data transmission among components.

5. Future Outlook

Existing cooperative control approaches focus on homogeneous USV clusters. Single-plane operational modes restrict the execution of three-dimensional maritime missions. Future research will evolve toward multi-domain heterogeneous coordination across air-sea-subsea domains. To establish comprehensive three-dimensional observation and operational networks, unifying spatiotemporal reference frames and integrating multi-source data among heterogeneous entities—such as Unmanned Aerial Vehicles (UAVs), underwater vehicles, and USVs—are required.

Physical models exhibit limitations under extreme sea conditions, and purely data-driven methods demonstrate weak generalization capabilities. A hybrid modeling paradigm driven by both mechanisms and data will address these limitations. Technologies such as physics-informed neural networks are introduced to correct model drift in real time. By endowing control systems with adaptive evolution capabilities in dynamic environments—including shallow-water effects and strong nonlinear wave-current coupling—is key to achieving high-precision navigation across all weather conditions and sea areas.

As algorithmic complexity increases and edge computing resources become constrained, lightweight computing architectures and human-machine synergy strategies are required. Future system design will integrate human operators' experiential intuition with machines' efficient execution. This human-machine hybrid augmented intelligence reduces computational load while enhancing decision resilience and reliability under crises and uncertain risks.

6. Conclusion

This survey reviews the core technological framework for autonomous multi-USV coordination in complex environments, encompassing modeling, decision planning, and security defense. Distributed optimization and intelligent control strategies mitigate multi-objective conflicts under strong nonlinear disturbances. The physical constraints of communication bandwidth, alongside the coupled effects of physical failures and malicious cyberattacks, restrict the reliability of cluster operations. Continuous innovations in computing and communication technologies may break through the strict assumptions of traditional control schemes regarding resources and environments, offering new opportunities to address these complex issues.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

Reference

[1] Liu, Z., Zhang, Y., Yu, X., & Yuan, C. (2016). Unmanned surface vehicles: An overview of developments and challenges. Annual Reviews in Control, 41, 71～93. https://doi.org/10.1016/j.arcontrol.2016.04.018

[2] Do, K. D., Jiang, Z. P., & Pan, J. (2002). Underactuated ship global tracking under relaxed conditions. IEEE Transactions on Automatic Control, 47(9), 1529～1536. https://doi.org/10.1109/TAC.2002.802755

[3] Qu, Y., Zhao, W., Yu, Z., & Xiao, B. (2022). Distributed prescribed performance containment control for unmanned surface vehicles based on disturbance observer. ISA Transactions, 125, 699～706. https://doi.org/10.1016/j.isatra.2021.12.007

[4] Park, J., Kang, M., Lee, Y., Jung, J., Choi, H.-T., & Choi, J. (2023). Multiple Autonomous Surface Vehicles for Autonomous Cooperative Navigation Tasks in a Marine Environment: Development and Preliminary Field Tests. IEEE

Access, 11, 36203～36217. https://doi.org/10.1109/ACCESS.2023.3262985
[5] Dong, Z., Liang, X., Liu, D., Yu, C., & Li, W. (2024). Dynamic formation optimisation for energy saving of a fleet of unmanned surface vehicles based on robust optimisation over time strategy. Ocean Engineering, 301, 117382. https://doi.org/10.1016/j.oceaneng.2024.117382
[6] Fossen, T. I. (2011). Handbook of marine craft hydrodynamics and motion control. Wiley.
[7] Bian, X., Fu, M., & Wang, Y. (2011). Chuan bo dong li ding wei [Ship dynamic positioning]. Science Press.
[8] Peng, Z., Wang, J., Wang, D., & Han, Q.-L. (2021). An Overview of Recent Advances in Coordinated Control of Multiple Autonomous Surface Vehicles. IEEE Transactions on Industrial Informatics, 17(2), 732 ～ 745. https://doi.org/10.1109/TII.2020.3004343
[9] Zhang, Chengqian, Zhang, Chi, Thies, F., Mao, W., & Ringsberg, J. W. (2025). A voyage planning framework for energy performance analysis of autonomous inland waterway vessels. Energy, 335, 137906. https://doi.org/10.1016/j.energy.2025.137906
[10] Yang, Y., & El Moctar, O. (2024). A mathematical model for ships maneuvering in deep and shallow waters. Ocean Engineering, 295, 116927. https://doi.org/10.1016/j.oceaneng.2024.116927
[11] Liu, Z., Lin, Z., Tao, L., & Lan, J. (2016). Nonlinear Wave–Current Interaction in Water of Finite Depth. Journal of Waterway, Port, Coastal, and Ocean Engineering, 142(6), 04016009. https://doi.org/10.1061/(ASCE)WW.1943-5460.0000345
[12] Xu, F., Gu, N., Peng, Z., Han, B., & Zhang, W. (2026). Collision-Free Reach-Avoid Differential Game of Multiple Underactuated Autonomous Surface Vehicles via Control Barrier Functions. IEEE Transactions on Intelligent Vehicles, 11(1), 42～51. https://doi.org/10.1109/TIV.2025.3578928
[13] Xiao, D., Song, Z., Zhai, M., & Jiang, N. (2025). Distributed multiple unmanned surface vehicles path planning integrated control framework in complex scenarios. Computers and Electrical Engineering, 124, 110430. https://doi.org/10.1016/j.compeleceng.2025.110430
[14] Shi, J., & Ye, M. (2024). Distributed Optimal Formation Control for Unmanned Surface Vessels by a Regularized Game-Based Approach. IEEE/CAA Journal of Automatica Sinica, 11(1), 276～278. https://doi.org/10.1109/JAS.2023.123930
[15] MahmoudZadeh, S., Abbasi, A., Yazdani, A., Wang, H., & Liu, Y. (2022). Uninterrupted path planning system for Multi-USV sampling mission in a cluttered ocean environment. Ocean Engineering, 254, 111328. https://doi.org/10.1016/j.oceaneng.2022.111328
[16] Yin, S., Xu, N., Shi, Z., & Xiang, Z. (2025). Collaborative path planning of multi-unmanned surface vehicles via multi-stage constrained multi-objective optimization. Advanced Engineering Informatics, 65, 103115. https://doi.org/10.1016/j.aei.2025.103115
[17] Wang, H., Fu, Z., Zhou, J., Fu, M., & Ruan, L. (2021). Cooperative collision avoidance for unmanned surface vehicles based on improved genetic algorithm. Ocean Engineering, 222, 108612. https://doi.org/10.1016/j.oceaneng.2021.108612
[18] Wu, Y., Low, K. H., & Lv, C. (2020). Cooperative Path Planning for Heterogeneous Unmanned Vehicles in a Search-and-Track Mission Aiming at an Underwater Target. IEEE Transactions on Vehicular Technology, 69(6), 6782～6787. https://doi.org/10.1109/TVT.2020.2991983
[19] Yao, P., Lou, Y., & Zhang, K. (2023). Multi-USV cooperative path planning by window update based self-organizing map and spectral clustering. Ocean Engineering, 275, 114140. https://doi.org/10.1016/j.oceaneng.2023.114140
[20] Luo, J., & Su, Y. (2024). Path planning for Multi-USV target coverage in complex environments. Ocean Engineering, 312, 119090. https://doi.org/10.1016/j.oceaneng.2024.119090
[21] Wu, F., Su, X., Cheng, T., Xu, H., & Wu, B. (2025). Ship Formation Control Using Nonlinear Model Predictive Control With Safe Speed Constraints and Tidal Elevation Variations. IET Intelligent Transport Systems, 19(1), e70082. https://doi.org/10.1049/itr2.70082
[22] Chen, L., Hopman, H., & Negenborn, R. R. (2018). Distributed model predictive control for vessel train formations of cooperative multi-vessel systems. Transportation Research Part C: Emerging Technologies, 92, 101 ～ 118. https://doi.

org/10.1016/j.trc.2018.04.013

[23] Zhu, Y., Li, Z., Li, Y., Yuan, C., & Guo, G. (2025). Multi-target tracking and surrounding control for multi-USV system under unknown disturbances based on distributed NMPC. Ocean Engineering, 338, 121972. https://doi.org/10.1016/j.oceaneng.2025.121972

[24] Du, Z., Negenborn, R. R., & Reppa, V. (2023). Distributed Dynamic Coordination Control for Offshore Platform Transportation Under Ocean Environmental Disturbances. IEEE Transactions on Control Systems Technology, 31(5), 2093～2106. https://doi.org/10.1109/TCST.2023.3291557

[25] Du, Z., Negenborn, R. R., & Reppa, V. (2022). COLREGS-Compliant collision avoidance for physically coupled multi-vessel systems with distributed MPC. Ocean Engineering, 260, 111917. https://doi.org/10.1016/j.oceaneng.2022.111917

[26] Tran, H. A., Lauvås, N., Johansen, T. A., & Negenborn, R. R. (2025). Asynchronous Distributed Collision Avoidance With Intention Consensus for Inland Autonomous Ships. IEEE Transactions on Control Systems Technology, 33(6), 2410～2425. https://doi.org/10.1109/TCST.2025.3587842

[27] Wang, C.-C., Wang, Y.-L., Shi, P., & Wang, F. (2024). Scalable-MADDPG-Based Cooperative Target Invasion for a Multi-USV System. IEEE Transactions on Neural Networks and Learning Systems, 35(12), 17867～17877. https://doi.org/10.1109/TNNLS.2023.3309689

[28] Wang, C.-C., Wang, Y.-L., Han, Q.-L., & Xie, W.-B. (2025). Multi-USV Cooperative Formation Control via Deep Reinforcement Learning With Deceleration. IEEE Transactions on Intelligent Vehicles, 10(3), 1909～1918. https://doi.org/10.1109/TIV.2024.3437735

[29] Xiao, R., Liu, C., Chen, H., Xu, L., & Zhang, Y. (2025). Value decomposition reinforcement learning-based formation control for multi-USVs with incomplete information. Ocean Engineering, 342, 123056. https://doi.org/10.1016/j.oceaneng.2025.123056

[30] Xue, S., Zhao, N., Wang, L., Zhang, W., Zhang, J., & Zhu, F. (2025). Multi-agent self-attention reinforcement learning for multi-USV hunting target. Neural Networks, 189, 107574. https://doi.org/10.1016/j.neunet.2025.107574

[31] Qu, X., Jiang, Y., Zhang, R., & Long, F. (2023). A Deep Reinforcement Learning-Based Path-Following Control Scheme for an Uncertain Under-Actuated Autonomous Marine Vehicle. Journal of Marine Science and Engineering, 11(9), 1762. https://doi.org/10.3390/jmse11091762

[32] Wang, N., Gao, Y., Yang, C., & Zhang, X. (2022). Reinforcement learning-based finite-time tracking control of an unknown unmanned surface vehicle with input constraints. Neurocomputing, 484, 26 ～ 37. https://doi.org/10.1016/j.neucom.2021.04.133

[33] Peng, Z., Liu, E., Pan, C., Wang, H., Wang, D., & Liu, L. (2023). Model-based deep reinforcement learning for data-driven motion control of an under-actuated unmanned surface vehicle: Path following and trajectory tracking. Journal of the Franklin Institute, 360(6), 4399～4426. https://doi.org/10.1016/j.jfranklin.2022.10.020

[34] Liu, Y., Chen, C., Qu, D., Zhong, Y., Pu, H., Luo, J., Peng, Y., Xie, J., & Zhou, R. (2023). Multi-USV System Antidisturbance Cooperative Searching Based on the Reinforcement Learning Method. IEEE Journal of Oceanic Engineering, 48(4), 1019～1047. https://doi.org/10.1109/JOE.2023.3281630

[35] Chen, L., Wangu, Y., Miao, Z., Jiang, Y., Wang, X., & Dai, S.-L. (2025). Identifier-Critic-Based Adaptive Optimal Control for USVs With Guaranteed Performance. IEEE Transactions on Artificial Intelligence, 1 ～ 12. https://doi.org/10.1109/TAI.2025.3640155

[36] Yuan, L.-E., Xiao, Y., Li, T., & Zhou, D. (2024). Output Feedback Adaptive Optimal Control of Multiple Unmanned Marine Vehicles with Unknown External Disturbance. Journal of Marine Science and Engineering, 12(10), 1697. https://doi.org/10.3390/jmse12101697

[37] Xue, S., Zhao, N., Zhang, W., Luo, B., & Liu, D. (2025). A Hybrid Adaptive Dynamic Programming for Optimal Tracking Control of USVs. IEEE Transactions on Neural Networks and Learning Systems, 36(6), 9961～9969. https://doi.org/10.1109/TNNLS.2024.3512539

[38] Li, G., Cao, L., Wang, W., Li, X., & Bai, W. (2025). Neural network-based collision-free optimal formation control for

unmanned surface vehicles with the gain iterative disturbance observer. Information Sciences, 719, 122438. https://doi.org/10.1016/j.ins.2025.122438

[39] Lyu, G., Peng, Z., & Wang, J. (2025). Safety-Certified Parallel Model Predictive Control of Autonomous Surface Vehicles via Neurodynamic Optimization. IEEE/CAA Journal of Automatica Sinica, 12(10), 2056 ～ 2066. https://doi.org/10.1109/JAS.2024.124980

[40] Qin, J., & Du, J. (2023). Minimum-learning-parameter-based adaptive finite-time trajectory tracking event-triggered control for underactuated surface vessels with parametric uncertainties. Ocean Engineering, 271, 113634. https://doi.org/10.1016/j.oceaneng.2023.113634

[41] Chu, S., & Li, N. (2024). Distributed Composite Learning Adaptive Fault-Tolerant Control for Multiple Marine Vehicles With Event-Triggered Communication. IEEE Transactions on Intelligent Transportation Systems, 25(6), 5664 ～ 5673. https://doi.org/10.1109/TITS.2023.3340746

[42] Wu, W., & Tong, S. (2024). Collision-Free Finite-Time Adaptive Fuzzy Output-Feedback Formation Control for Unmanned Surface Vehicle Systems. IEEE Transactions on Intelligent Vehicles, 9(1), 1094 ～ 1103. https://doi.org/10.1109/TIV.2023.3335467

[43] Hu, X., Zhu, G., Ma, Y., Li, Z., Malekian, R., & Sotelo, M. Á. (2023). Dynamic Event-Triggered Adaptive Formation With Disturbance Rejection for Marine Vehicles Under Unknown Model Dynamics. IEEE Transactions on Vehicular Technology, 72(5), 5664～5676. https://doi.org/10.1109/TVT.2022.3231585

[44] Ning, J., Ma, Y., & Chen, C. L. P. (2025). Event-Triggered-Based Distributed Formation Cooperative Tracking Control of Under-Actuated Unmanned Surface Vehicles With Input and State Quantization. IEEE Transactions on Intelligent Transportation Systems, 26(5), 7081～7097. https://doi.org/10.1109/TITS.2024.3524442

[45] Bo, P., Li, S., Tu, W., Guo, Q., & Luo, J. (2025). Event-Based H∞ Filtering for Networked Mass-Switching AMVs: An Augmented Lyapunov Functional Approach. IEEE Internet of Things Journal, 12(24), 53055 ～ 53069. https://doi.org/10.1109/JIOT.2025.3615154

[46] Ning, J., Wang, Y., Liu, L., & Li, T. (2025). Quantized state feedback adaptive trajectory tracking control of Unmanned Surface Vehicle with state and input quantization. Journal of the Franklin Institute, 362(12), 107654. https://doi.org/10.1016/j.jfranklin.2025.107654

[47] Xu, Q., Feng, L., & Yao, L. (2024). Cooperative Adaptive Tracking Control Based on Quantized States for Multiple Surface Vessels. IEEE Access, 12, 5117～5131. https://doi.org/10.1109/ACCESS.2024.3350189

[48] Wang, W., Wang, Y., & Li, T. (2024). Distributed Formation Maneuvering Quantized Control of Under-Actuated Unmanned Surface Vehicles with Collision and Velocity Constraints. Journal of Marine Science and Engineering, 12(5), 848. https://doi.org/10.3390/jmse12050848

[49] Park, B. S., & Yoo, S. J. (2022). Quantized-communication-based neural network control for formation tracking of networked multiple unmanned surface vehicles without velocity information. Engineering Applications of Artificial Intelligence, 114, 105160. https://doi.org/10.1016/j.engappai.2022.105160

[50] Gu, N., Wang, D., Peng, Z., Wang, J., & Han, Q.-L. (2022). Disturbance observers and extended state observers for marine vehicles: A survey. Control Engineering Practice, 123, 105158. https://doi.org/10.1016/j.conengprac.2022.105158

[51] Fu, M., & Yu, L. (2018). Finite-time extended state observer-based distributed formation control for marine surface vehicles with input saturation and disturbances. Ocean Engineering, 159, 219 ～ 227. https://doi.org/10.1016/j.oceaneng.2018.04.016

[52] Wu, T., Liu, Z., Shi, G., & Yu, S. (2023). Robust adaptive output feedback for the formation control of heterogeneous ships based on a nonlinear extended state observer. Ocean Engineering, 289, 116235. https://doi.org/10.1016/j.oceaneng.2023.116235

[53] Ma, Y., Ning, J., Li, T., & Liu, L. (2024). Distributed extended state observer based formation tracking control of under-actuated unmanned surface vehicles with input and state quantization. Ocean Engineering, 311, 118872. https://doi.org/10.1016/j.oceaneng.2024.118872

[54] Luo, Q., Wang, H., Li, N., & Zheng, W. (2024). Multi-unmanned surface vehicle model-free sliding mode predictive adaptive formation control and obstacle avoidance in complex marine environment via model-free extended state observer. Ocean Engineering, 293, 116773. https://doi.org/10.1016/j.oceaneng.2024.116773

[55] Liu, Z., Gong, Q., Hu, X., Zhu, G., Guo, S., Ma, B., & Li, X. (2025). Practical fixed-time formation control with disturbance rejection for marine vehicles under input saturation. ISA Transactions, 164, 100 ～ 115. https://doi.org/10.1016/j.isatra.2025.05.032

[56] Jiang, Y., Wang, F., Yu, H., Guo, C., & Liu, Z. (2023). Adaptive prescribed-time containment control for multiple unmanned surface vehicles with uncertain dynamics and actuator dead-zones. Ocean Engineering, 289, 116269. https://doi.org/10.1016/j.oceaneng.2023.116269

[57] Xia, G., Sun, C., Zhao, B., Sun, X., & Xia, X. (2022). Robust cooperative trajectory tracking control for an unactuated floating object with multiple vessels system. ISA Transactions, 123, 263 ～ 271. https://doi.org/10.1016/j.isatra.2021.05.043

[58] Jia, Z., Lu, H., Chen, H., & Zhang, W. (2024). Robust Distributed Cooperative Rendezvous Control for Heterogeneous Marine Vehicles Using Model Predictive Control.

[59] Li, J., Zhang, G., Zhang, W., & Zhang, X. (2024). Robust control for cooperative path following of marine surface-air vehicles with a constrained inter-vehicles communication. Ocean Engineering, 308, 118240. https://doi.org/10.1016/j.oceaneng.2024.118240

[60] Liu, C., Chen, H., Jiang, B., Zhang, Y., & Xie, S. (2025). Adaptive Reconfigurable Fault-Tolerant Control of Multi-USVs With Actuator Magnitude and Rate Faults. IEEE Transactions on Industrial Electronics, 72(8), 8512 ～ 8521. https://doi.org/10.1109/TIE.2025.3528508

[61] Wang, Y., & Liu, C. (2023). Distributed finite-time adaptive fault-tolerant formation–containment control for USVs with dynamic event-triggered mechanism. Ocean Engineering, 280, 114524. https://doi.org/10.1016/j.oceaneng.2023.114524

[62] Li, K., Feng, K., & Li, Y. (2024). Fuzzy Adaptive Fault-Tolerant Formation Control for USVs With Intermittent Actuator Faults. IEEE Transactions on Intelligent Vehicles, 9(3), 4445～4455. https://doi.org/10.1109/TIV.2024.3358351

[63] Wu, C., Zhu, G., & Lu, J. (2023). Indirect adaptive neural tracking control of USVs under injection and deception attacks. Ocean Engineering, 270, 113641. https://doi.org/10.1016/j.oceaneng.2023.113641

[64] Jiang, Y., Wang, L., Sun, J., & Yu, H. (2024). Attack-resistant distributed formation control for multiple unmanned surface vessels subject to output constraints. Ocean Engineering, 314, 119712. https://doi.org/10.1016/j.oceaneng.2024.119712

[65] Han, S., Zhu, H., Zhong, Q., Shi, K., & Kwon, O.-M. (2024). Secure Sampled-Data Consensus of Multi-Agent Systems Under Asynchronous Deception Attacks With Application to Unmanned Surface Vehicles. IEEE Transactions on Intelligent Transportation Systems, 25(6), 5462～5473. https://doi.org/10.1109/TITS.2023.3330995

[66] Sun, H., Liu, X., & Hou, L. (2025). Event-triggered observer-based dynamic positioning control of unmanned marine vehicle systems under deception attack. Journal of the Franklin Institute, 362(15), 108002. https://doi.org/10.1016/j.jfranklin.2025.108002

[67] Wang, Q., Liu, C., Lan, J., Ren, X., Meng, Y., & Wang, X. (2024). Distributed Secure Surrounding Control for Multiple USVs Against Deception Attacks: A Stackelberg Game Approach With Reinforcement Learning. IEEE Transactions on Intelligent Vehicles, 9(11), 7003～7015. https://doi.org/10.1109/TIV.2024.3392423

[68] Zhong, Q., Han, S., Shi, K., Cai, X., Kwon, O.-M., & Zhong, S. (2022). Secure consensus switching control for multiagent system under abnormal deception attacks and its application to unmanned surface vehicle clusters. Expert Systems with Applications, 205, 117702. https://doi.org/10.1016/j.eswa.2022.117702

[69] Ma, Y., Qi, X., Li, Z., Hu, S., & Sotelo, M. Á. (2024). Resilient Control for Networked Unmanned Surface Vehicles With Dynamic Event-Triggered Mechanism Under Aperiodic DoS Attacks. IEEE Transactions on Vehicular Technology, 73(4), 5824～5833. https://doi.org/10.1109/TVT.2023.3334694

[70] Li, X., Shi, P., & Zhang, W. (2023). Adaptive event-triggered based fault detection filtering for unmanned surface

vehicles under DoS attacks. Journal of the Franklin Institute, 360(17), 13051 ～ 13079. https://doi.org/10.1016/j.jfranklin.2023.09.047

[71] Zhang, D., Liu, K., Yang, Y., & Li, T. (2025). Dynamic Event-Based Affine Formation Maneuver Control for Multi-ASV Systems Under DoS Attacks. IEEE Transactions on Vehicular Technology, 1 ～ 12. https://doi.org/10.1109/TVT.2025.3616498

[72] Zhang, J., Liu, K., Yang, Y., Li, T., & Jia, Z. (2025). Event-based multi-target enclosing control for multi-ASV systems under DoS attacks. Ocean Engineering, 338, 121989. https://doi.org/10.1016/j.oceaneng.2025.121989

[73] Wu, X., Zong, G., Wang, H., Niu, B., & Zhao, X. (2025). Collision-Free Distributed Adaptive Resilient Formation Control for Underactuated USVs Subject to Intermittent Actuator Faults and Denial-of-Service Attacks. IEEE Transactions on Vehicular Technology, 74(9), 13606～13617. https://doi.org/10.1109/TVT.2025.3565820

[74] Feng, N., Wu, D., Yu, H., You, Z., & Tu, W. (2025). Disturbance rejection event-triggered robust nonlinear model predictive control for underactuated unmanned surface vehicle against DoS attacks without velocity measurements. ISA Transactions, 167, 194～205. https://doi.org/10.1016/j.isatra.2025.08.031