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Review

A Review of Path Following, Trajectory Tracking, and Formation Control for Autonomous Underwater Vehicles

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Abstract: This paper summarizes the latest research progress in the field of motion control of autonomous underwater vehicles (AUVs), focusing on three core technologies: path following, trajectory tracking and multi-AUV formation control. Aiming at the external disturbances faced by AUVs performing tasks in complex marine environments as well as the system's own inherent nonlinearities, model uncertainties, and physical constraints, it analyzes the advantages and shortcomings of the traditional control methods and intelligent control strategies in terms of improving the tracking accuracy, enhancing the robustness of the system, and realizing the cooperative operation. Recent advances in distributed control and multi-AUV cooperative operations, including leader–follower, consistency control, virtual structure and behavior control, and other formation control strategies, are also discussed. Finally, the future development trend of AUV control technology is outlooked, pointing out that intelligent control, multi-sensor fusion navigation, and distributed synergy will become an important direction to enhance the operational capability and adaptability of AUVs. This review aims to provide theoretical references and technical support for AUV applications in the fields of marine resource exploration and environmental monitoring.

Keywords: AUV; motion control; path following; trajectory tracking; formation control

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Academic Editor: Mostafa Hassanalian

Received: 6 March 2025
Revised: 31 March 2025
Accepted: 7 April 2025
Published: 8 April 2025

Citation: He, L.; Xie, M.; Zhang, Y. A Review of Path Following, Trajectory Tracking, and Formation Control for Autonomous Underwater Vehicles. *Drones* **2025**, *9*, 286. https://doi.org/10.3390/drones9040286

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1. Introduction

In recent years, underwater exploration and operation technologies have been increasingly widely used in the fields of marine science, resource exploration, environmental monitoring, and the military [1]. Among them, underwater vehicles, as the core equipment, have become an important tool for exploring the deep sea and obtaining key data [2]. According to different levels of autonomy, underwater vehicles can be divided into manned underwater vehicles and unmanned underwater vehicles. Unmanned underwater vehicles can be further categorized into remotely operated underwater vehicles (ROVs) with cables and autonomous underwater vehicles (AUVs) without cables. AUVs occupy an important position in marine autonomous system applications due to their high autonomy and flexibility. In the field of marine geoscience, AUVs were initially applied to seafloor topographic mapping, and with continuous technological advancements, their applications have gradually expanded to water column geochemistry, oceanographic measurements, and oceanographic data acquisition [3,4]. In addition, AUVs have also shown great potential in the fields of marine resource exploration [5], environmental monitoring [6], underwater archeology [7], and military reconnaissance [8,9]. For example, in marine resource exploration, AUVs can carry a variety of sensors and go deep into the seabed for resource exploration and data collection. In environmental monitoring, AUVs can monitor

changes in the marine environment over long periods and wide areas to provide data support for environmental protection. In military reconnaissance, AUVs can carry out covert reconnaissance missions to provide crucial information for military decision-making. Reference [10] comprehensively reviews the research progress of autonomous underwater vehicles, covering key areas such as structural design, propulsion technology, dynamics modeling, control methods, navigation and localization technology, and underwater communication.

The smooth execution of these tasks by AUVs relies on the guidance, navigation, and control systems [11–14]. Motion control, as the core of AUV task execution, directly affects navigation accuracy, operational efficiency, and environmental adaptability. According to different control objectives, the motion control of AUVs can be broadly categorized into path following [15–25], trajectory tracking [26–38], and formation control [39–50]. Path following emphasizes sailing along a preset route and focuses on overall heading, whereas trajectory tracking requires the AUV to move strictly along a predetermined curved or zigzagging trajectory, performing the mission with a specific attitude and speed [51,52]. However, in practical operations, a single AUV often struggles to perform large-scale and complex missions due to its limited energy and load capacity. As a result, multi-AUV formation operations have become an important development trend. Through formation control technology, multiple AUVs can move together underwater in a set formation, thereby enhancing operational efficiency, expanding the operational range, and reducing overall cost [53,54]. In the oil and gas industry, multi-AUV formations can collaborate to accomplish subsea pipeline inspections and resource exploration tasks, significantly improving operational efficiency and data quality. In hydrographic surveys, multi-AUV formations can collect data simultaneously from multiple locations, enhancing survey coverage and accuracy. In military missions, multi-AUV formations can perform complex reconnaissance and surveillance tasks, improving mission flexibility and success rates. Overall, multi-AUV systems have demonstrated higher stability and execution power compared to individual AUVs in areas such as oil and gas exploration, hydrographic surveys, and military operations, making them an important direction for the development of marine intelligent equipment [55,56].

With the expanding mission scope of AUVs, it is difficult for traditional control methods (e.g., sliding-mode control, model predictive control, backpropagation, etc.) to meet the demands of diversified and complex missions. Traditional control methods for AUVs are less adaptive in the face of the complex marine environment; e.g., it is difficult for PID control to deal with the nonlinear system and time-varying disturbances. Meanwhile, the control performance of traditional control methods decreases significantly when facing communication delays and interruptions, and the introduction of intelligent control methods can better cope with communication problems through predictive mechanisms and robust design. Intelligent control is a control method that combines traditional control theory and modern intelligent technology, aiming to solve the control problems of complex systems by simulating human intelligence. It is not only able to deal with nonlinear, uncertain and dynamically changing systems, but also has the ability of self-adaptation, self-learning and self-organization. Up to now, AUV motion control technology has attracted the attention of many scholars and has resulted in a large number of research results on an international scale. These studies cover many aspects from basic control algorithms to intelligent optimization methods, and some representative papers are summarized in Table 1. The intelligent control methods commonly used in AUV motion control are summarized in Table 2, and their applications in path-following control, trajectory tracking control, and formation control are shown. A detailed comparison of the advantages and limitations

of different intelligent control methods is presented in Table 3, which provides the reader with a reference for selecting a suitable control method.

Table 1. Representative studies on AUV motion control.

Paper	Publication Year	Main Contents
[49]	2014	adaptive sliding-mode control for formation control
[17]	2016	path-following control via fuzzy backstepping sliding-mode control
[24]	2018	path-following control using adaptive second-order sliding-mode control
[46]	2018	formation control using adaptive self-organizing map neural network
[20]	2019	path-following control based on fuzzy sliding-mode control with radial basis function neural networks
[38]	2020	trajectory tracking control based on backstepping and adaptive sliding-mode control
[48]	2021	formation control based on reinforcement learning
[22]	2022	path-following control integrating reinforcement learning and dynamic data-driven models
[35]	2022	trajectory control using rapidly deployed deep reinforcement learning
[54]	2023	formation transformation control algorithm based on leader–follower strategy
[25]	2024	3d path-following control method based on backstepping sliding-mode control
[33]	2025	trajectory tracking control method based on adaptive sliding-mode control using backstepping and neural networks

Table 2. Intelligent control methods for AUVs.

Control Methods	Path-Following Control	Trajectory Tracking Control	Formation Control
fuzzy logic control	[17–19]	[25–31]	[43–45]
neural network control	[20,21]	[33,34]	[46,47]
reinforcement learning control	[22,23]	[35–37]	[48]
adaptive dynamic programming control	[24]	[38]	[48]

Table 3. Comparative analysis of intelligent control methods for AUVs.

Intelligent Control Method	Advantages	Disadvantages
fuzzy logic control	handle uncertainties [18,24,28], no precise model needed [18,26], strong robustness [24,29]	complex rule design [18,28], high computational cost [24,28], no guarantee of global optimum [18,26]
neural network control	adaptability [20,33,34], strong nonlinear mapping ability [20,33], data-driven [20,34]	large training data requirement [20,34], risk of overfitting [20,33], poor interpretability
reinforcement learning control	self-learning [21,23,36], ability to adapt to complex environments [21,35,37], long- term optimization [21,36]	slow convergence [20,34], difficulty in balancing exploration and exploitation [20,23], sensitivity to initial conditions [21,36]
adaptive dynamic programming control	online parameter tuning [24,32,38], strong robustness [24,29], suitability for unknown systems [24,32]	complex design [24,32], stability issues [24,29], high computational cost [24,32]

The purpose of this paper is to review the research progress of AUVs in the three major directions of path following, trajectory tracking, and formation coordination; summarize

the current key technologies; and analyze the future research trends. This review aims to provide a valuable reference for the study and development of motion control technology for underwater vehicles. The main contributions of this paper are as follows:

(1) A comprehensive review of AUV motion control technology is conducted, covering the three core directions of path following, trajectory tracking, and formation control. The characteristics, applicable scenarios, advantages, and limitations of various motion control methods are summarized in detail. In addition, a systematic classification of different control methods is conducted and we summarize the control strategies proposed to address these problems.
(2) The main problems and challenges in the field of AUV motion control are identified and summarized. These include environmental adaptation problems and system characterization problems. The impact of key factors in the marine environment on AUV motion control is discussed in depth. Additionally, the constraints imposed by AUV system characteristics, such as nonlinear dynamics, dynamic coupling, and model uncertainty, are analyzed in the context of motion control.
(3) The shortcomings of current research are summarized, and future development trends are anticipated. These trends include the further development of intelligent control methods, the optimization of multi-AUV cooperative operations, and the enhancement of adaptability to complex environments.

The rest of the paper is organized as follows: Section 2 introduces the current research status and development trend of AUV motion control methods; Section 3 analyzes the challenges faced by AUV motion control, discusses the strengths and weaknesses of the existing research, and proposes future research directions; Section 4 provides a concluding review of the whole paper. The terms used in the text are listed in Appendix A.

2. AUV Motion Control Methods

This section will thoroughly review the key methods for path-following control, trajectory tracking control, and formation control of AUVs. We will analyze each method's characteristics, suitable scenarios, strengths, and limitations. Our goal is to offer a clear, comparative summary of these motion control strategies, examining not only their technical principles but also their practical trade-offs in real-world underwater applications. To aid direct comparison, we will assess each method across key performance features such as robustness, adaptability, computational efficiency, and ease of implementation.

Path-following control aims to make AUVs navigate along a preset path, focusing primarily on minimizing position error [16,25]. Trajectory tracking control requires AUVs not only to follow a specified trajectory but also to arrive at a predetermined position at a specific time, thus imposing higher demands for spatio-temporal consistency [57,58]. Formation control involves the coordinated motion of multiple AUVs to ensure that formation members maintain established relative positions and formations during mission execution, thereby enhancing operational efficiency and system robustness [40,46]. In recent years, researchers have proposed a variety of methods for AUV motion control, including classical control methods (e.g., PID control), modern nonlinear control methods (e.g., sliding-mode control, model predictive control), and artificial intelligence-based control methods (e.g., reinforcement learning, neural network control). In addition, in multi-AUV systems, researchers have further developed various formation control strategies, such as leader–follower control, consensus control, virtual structure control, and behavior-based control, to improve the autonomy and mission adaptability of the system.

2.1. Path-Following Control

The core task of path following is to make the AUV move along a predefined path, minimizing the positional error while avoiding collisions and uncertainties in a dynamic environment. As shown in Figure 1, $\{E\} : O_E - \xi\eta\zeta$, $\{B\} : O_B - x_b y_b z_b$ and $\{SF\} : O_{SF} - x_{sf} y_{sf} z_{sf}$ denote the geodetic coordinate system, the body coordinate systems and the path coordinate system, respectively; the origin of $\{SF\}$ serves as the reference point for path following. An underactuated AUV follows a predefined 3D spatial path $\eta_f(s) = \left[x_f(s)\ y_f(s)\ z_f(s)\right]^{\mathrm{T}} \in \mathbb{R}^3$, which is parameterized by the variable s. The kinematics and dynamics of the AUV are described by the following model:

$$\begin{cases} \dot{\eta} = J(\eta)V \\ M\dot{V} + C(V)V + D(V)V + g(\eta) = \tau + \tau_e \end{cases} \tag{1}$$

where $\eta = [x\ \ y\ z\ \phi\ \theta\ \psi]^{\mathrm{T}}$, x, y, and z represent the geodetic coordinates of the AUV. ϕ, θ, ψ represent the Euler angles. $V = [u\ v\ w\ p\ q\ r]^{\mathrm{T}}$ is the velocity vector of the AUV. $J(\eta)$ represents the transformation matrix from $\{B\}$ to $\{E\}$. M is the inertia matrix. $C(V)$ represents the matrix of Göttinger and centripetal forces. $D(V)$ is the hydrodynamic damping matrix. $g(\eta)$ represents the restoring force and moment vector. τ is the control force and moment vector. τ_e is the environmental disturbance force and moment vector.

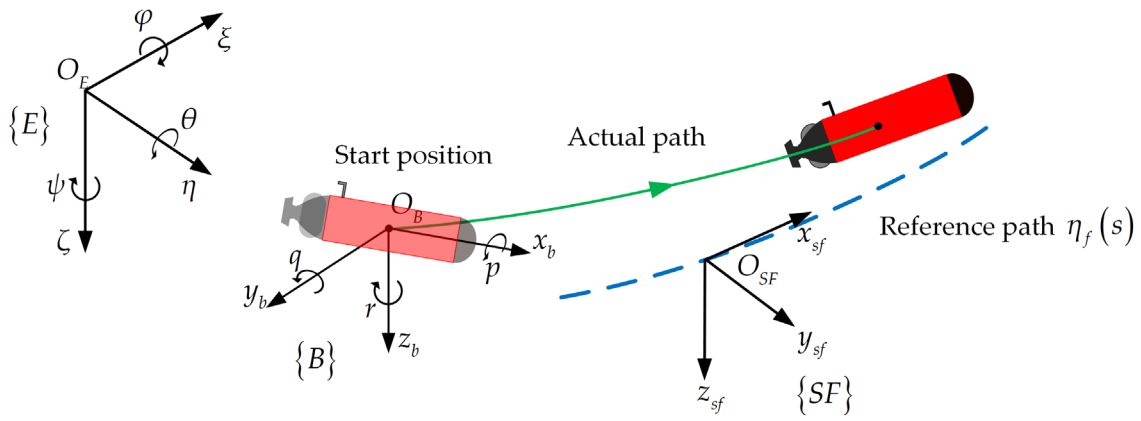


Figure 1. Diagram illustrating path following for AUVs.

The problem of path-following control can be formulated as follows:

Given a predefined path $\eta_f(s)$ in 3D space, considering the unknown environmental disturbances, we develop robust control laws for an underactuated AUV. This should ensure that the AUV's center of mass O_B asymptotically converges to the reference point O_{SF} and moves long the spatial path $\eta_f(s)$. Additionally, the control laws guarantee that the AUV follows the path, aligns its velocity direction with the path's tangent vector, and tracks a desired profile speed simultaneously.

Currently, the research on path-following control techniques focuses on reducing errors, enhancing system robustness and adapting to dynamic environments, involving the following types of methods:

2.1.1. Classical PID Control and Its Extensions

PID control (proportional–integral–derivative control) is a classical linear controller for systems with simple dynamic characteristics. However, for AUVs with nonlinear characteristics and multivariate coupling, there are limitations in the performance of conventional PID control. To address these shortcomings, researchers have proposed a variety of extension methods. For example, combining PID control with fuzzy logic has shown promise; a

block diagram of fuzzy logic control is shown in Figure 2. Mao et al. [59] combined fuzzy logic and traditional PID control, adjusting the PID parameters through fuzzification to enable the system to adapt to environmental changes in real time. This approach improves the performance of path following in complex environments. There are also several academic systems that combine PID with optimization algorithms. Yang et al. [60] further used a genetic algorithm to optimize the PID parameters, combined with an LOS guidance algorithm to compensate for heading drift and lateral error. This approach significantly improves the accuracy and response speed of path following in a dynamic environment.

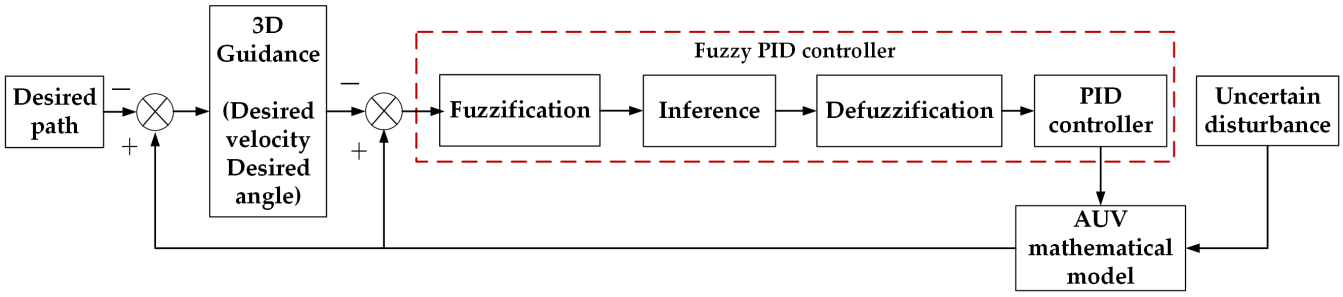


Figure 2. Block diagram of fuzzy logic control.

2.1.2. Sliding-Mode Control and Its Improvement

Sliding-mode control is a nonlinear control method known for its fast response and strong robustness. It achieves the control objective by designing a sliding-mode surface such that the system state slides on this surface. However, for complex nonlinear systems or strongly coupled systems, achieving the desired control effect with sliding-mode control alone can be challenging. In recent years, combining sliding-mode control with other intelligent control methods has become a popular research topic. Elmokadem et al. [61] proposed a robust control scheme based on sliding-mode control, achieving high efficiency in path following and compensating for environmental disturbances through the design of the sliding-mode surface. Rodriguez et al. [62] introduced an adaptive law to dynamically adjust the gain of the sliding-mode controller. Combined with a sliding-mode observer, this approach estimates uncertainties and further improves control accuracy. Backstepping sliding-mode control has significantly enhanced system robustness and fast convergence by recursively designing virtual control quantities and sliding-mode surfaces. Sun et al. [63] proposed a 3D path-following control method based on backstepping sliding-mode control. They combined backstepping and sliding-mode control, introduced a nonlinear disturbance observer to estimate and compensate for unknown disturbances, and dynamically adjusted the desired heading of the AUV using an adaptive guidance method. Building on backstepping-based sliding-mode control, Liang et al. [18] introduced fuzzy logic to dynamically adjust parameters in 2D path following, compensating for unknown disturbances. Jiang et al. [64] further designed an adaptive backstepping sliding-mode controller, introducing a parameter adaptive law to dynamically adjust control parameters and enhancing the system's anti-disturbance capability through a nonlinear disturbance observer. To estimate and compensate for system uncertainty disturbances in real time and enhance system robustness, He et al. [25] proposed a three-dimensional path-following control method based on an ocean current velocity observer. They designed a path-following control law combining sliding-mode control with a nonlinear disturbance observer to compensate for compound uncertainty disturbances. He et al. [65] proposed a path-following control method combining a nonlinear disturbance observer with an adaptive line-of-sight (LOS) method, which significantly improves the path-following performance of AUVs by estimating and compensating for system uncertainty disturbances in real time.

2.1.3. Model Predictive Control

Model predictive control (MPC) uses a system model to predict future states and achieves optimal results by optimizing control inputs. Its advantage is that it is suitable for complex nonlinear systems and multivariate control scenarios. However, its computational complexity and model dependency are high. Taniguchi et al. [66] addressed complex constraints in path following by predicting future states and optimizing control inputs based on a nonlinear MPC framework. Shen et al. [67] proposed a multi-objective MPC framework to solve the multi-objective optimization problem using two methods: weights and dictionary sequences. They transformed the path-following problem into a three-dimensional control problem of position and attitude, achieving high-accuracy tracking through an optimization algorithm. Wang et al. [68] combined inverse stepping sliding-mode control with MPC to design an inverse stepping sliding-mode controller for 3D path following of AUVs. This method optimizes control inputs and compensates for dynamic errors in real time. The nonlinear model predictive control in the above methods is computationally intensive when solving the nonlinear optimization problem in real time. Additionally, the control performance depends on the accuracy of the system model. Yao et al. [69] investigated an improved MPC method using nonlinear model predictive control to handle the dynamical nonlinearity and real-time requirements of AUVs. This method reduces the dependence on the accuracy of the system model and improves path-following performance by optimizing sensor data fusion.

2.1.4. Intelligent Controls

Reinforcement learning learns the optimal policy through the interaction between the agent and the environment, making it particularly suitable for solving complex decision-making problems in path following. A block diagram of reinforcement learning control is shown in Figure 3. Ma et al. [21] proposed a reinforcement learning-based control framework for AUV path following. They used a neural network model to learn the state transfer function and constructed a reinforcement learning controller. This controller enables the AUV to travel along the desired path by overcoming the dependence of traditional control methods on accurate system dynamics models, thereby achieving high-accuracy path following. Wang et al. [70] proposed a deep reinforcement learning-based offline optimal control method for AUV path following. This method uses a simplified deep deterministic policy gradient (DDPG) algorithm as the core of the control strategy and simplifies the neural network training process by considering only the reward of the current state. To address the problems of sparse rewards and low learning efficiency in traditional reinforcement learning methods, Jiang et al. [71] combined generative adversarial networks (GANs) with interactive reinforcement learning. By using the generator and discriminator of GANs to learn the state and action distributions of expert behaviors, they optimized the control strategy using human feedback. This approach significantly improved learning efficiency and adaptability. Zhang et al. [23] further applied deep interactive reinforcement learning to AUV path following. By combining human feedback and environmental rewards, they enhanced the AUV's autonomous decision-making ability in dynamic environments. However, since reward signals are often sparse, future research could focus on designing effective reward functions to further optimize the algorithm.

Different motion control methods have their own advantages and are suitable for different application scenarios. The main features are summarized in Table 4.

This section reviews major methods for AUV path-following control, including classical PID control, sliding-mode control, model predictive control, and intelligent methods such as reinforcement learning. Each approach has specific strengths in enhancing tracking accuracy and robustness but also faces limitations such as computational complexity or

sensitivity to modeling errors. Classical PID control is easy to implement but lacks adaptability. Sliding-mode control is robust but may introduce chattering and sensitivity to noise. Model predictive control provides optimality but suffers from high computational cost and model dependency. Intelligent controls show strong adaptability but require large training datasets and lack interpretability. A careful selection and hybridization of these techniques is often necessary in real-world applications.

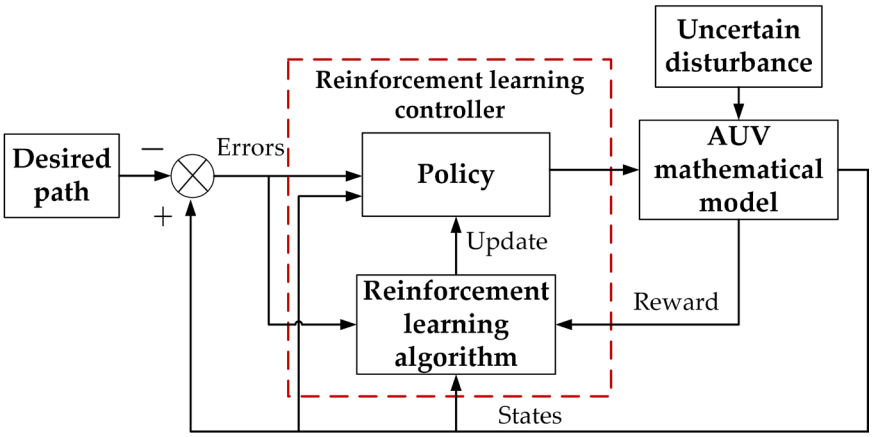


Figure 3. Block diagram of reinforcement learning control.

Table 4. Control methods for AUVs: application scenarios, strengths, and limitations.

Control Methods	Application Scenarios	Strengths	Limitations
PID control	path tracking and positioning [59] and simple dynamic systems [72]	wide applicability [59], strong robustness [60], simple to implement [72]	poor adaptability to nonlinear systems [59], limited dynamic performance [60], complex parameter tuning [58]
sliding-model control	nonlinear and uncertain systems [61], path tracking and dynamic positioning [62]	strong robustness [61], fast dynamic response [62], adaptation to complex dynamics [63]	high-frequency vibration problems [61], sensitivity to noise [62], high implementation complexity [63]
model predictive control	path planning and tracking [66], complex dynamic systems [67]	optimization ability [66], adaptation to complex dynamics [67], predictive ability [68]	difficulty in implementation [66], high computational complexity [68], reliance on precise models [69]
intelligent controls	complex tasks and dynamic environments [21], autonomous decision-making and optimization [70]	autonomous learning ability [21], adaptation to complex dynamics [70], high flexibility [71]	lack of real-time performance [23], high dependence on environment [21], long training time [70]

2.2. Trajectory Tracking Control

The goal of trajectory tracking is to enable the AUV to reach the predetermined spatial position at a specified time, thereby satisfying dual constraints of time and space. Compared with path following, trajectory tracking places greater emphasis on precise position control at each moment in time. As shown in Figure 4, the AUV needs to accurately follow the reference trajectory $\eta_r(t) = [x_r(t)\ y_r(t)\ z_r(t)]^{\mathrm{T}} \in \mathbb{R}^3$ in both the temporal and spatial dimensions. The reference trajectory can be defined as a time function of coordinates and Euler angles.

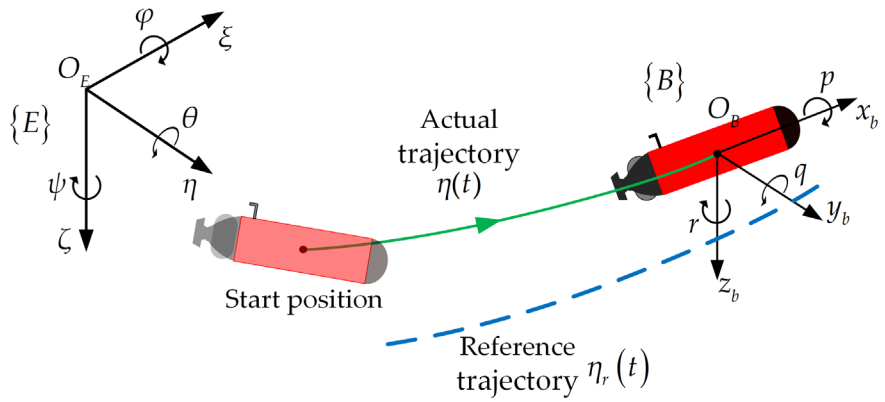


Figure 4. Diagram illustrating tracking control for AUVs.

The problem of trajectory tracking control can be formulated as follows:

Considering mathematical models (1) of an underactuated AUV, given a predefined bounded reference trajectory $\eta_r(t)$ in 3D space, and taking into account unknown environmental disturbances, the task is to design robust control laws that enable the AUV to reach and track the reference trajectory. The error between the actual trajectory $\eta(t)$ of the AUV and the reference trajectory $\eta_r(t)$ is defined as $e(t)$, which should converge to an arbitrarily small size while ensuring the stability of the trajectory tracking. This can be mathematically expressed as $\lim_{t\to\infty} \| e(t) \| = \lim_{t\to\infty} \| \eta(t) - \eta_r(t) \| \leq \delta$, where δ is an arbitrarily small positive constant. When error $e(t)$ converges to zero, it signifies the AUV has successfully tracked the reference trajectory.

2.2.1. Sliding-Mode Control

Sliding-mode control is a nonlinear control method that achieves tracking of a desired trajectory by designing a sliding-mode surface on which the system state slides. The main features of sliding-mode control include fast response, strong robustness, and effective compensation of system uncertainty. To improve robustness against external disturbances in complex environments, Elmokadem et al. [73] proposed a sliding-mode control scheme that introduces a nonlinear term to design the desired velocity and designs a sliding-mode control law to make the sliding-mode surface converge to zero in finite time. In marine environments with significant current disturbances, Jalalnezhad et al. [74] proposed a sliding-mode control-based AUV trajectory tracking method. This method significantly improves the trajectory tracking performance of the AUV in complex environments by designing the sliding-mode surface and control law and combining them with a disturbance observer to compensate for uncertainty disturbances in real time. When dealing with complex dynamics and external disturbances, Guo et al. [38] proposed a trajectory tracking control method based on the backstepping method. This method combines backstepping and adaptive sliding-mode control by designing the sliding-mode surface so that the system state slides on the surface, thereby enhancing the robustness of the system. Zhou et al. [57] proposed a trajectory tracking control method that combines backstepping and sliding-mode control. They introduced a state prediction mechanism to improve the trajectory tracking performance and robustness of the AUV.

2.2.2. Feedback Linearization and MPC

Feedback linearization control simplifies the control design by transforming a nonlinear system into a linear system through appropriate feedback transformations. Yon et al. [75] effectively solved the nonlinear trajectory tracking problem by transforming the nonlinear AUV model into affine form through feedback linearization and combining it

with model predictive control (MPC) to optimize the control inputs. Yan et al. [76] designed a distributed observer and model predictive controller. They transformed the mathematical model of the AUV into a standard dual-integrated dynamics model through feedback linearization to achieve trajectory tracking. Yue et al. [77] proposed a distributed model predictive control method. They converted the nonlinear AUV model into a linear model through feedback linearization for subsequent control design. Based on the linearized model, they designed a coordinated control strategy for multiple AUVs. This approach solves the trajectory tracking problem under nonconvex control input constraints and weak communication conditions.

2.2.3. Intelligent Controls

Neural network control is an advanced control method based on artificial neural networks, particularly suitable for solving unknown dynamic problems in nonlinear trajectory tracking through self-learning and adaptive capabilities. A block diagram of neural network control is shown in Figure 5. When dealing with 3D trajectory tracking tasks, Liang et al. [78] proposed a trajectory tracking method based on radial basis function (RBF) neural networks. They used RBF neural networks to approximate unknown functions online and designed adaptive laws to adjust the neural network's weights. This approach improves the control performance of AUVs in complex environments and is suitable for scenarios with high real-time requirements and limited computational resources. It can respond quickly and reduce computational burden. In [79], the application of neural networks in trajectory tracking, hybrid visual servo control and observer-based adaptive control is demonstrated. For remotely operated vehicles, an observer-based adaptive neural network control technique is proposed. A single-layer feed-forward neural network is utilized to compensate the dynamic uncertainty and combined with an adaptive sliding-mode controller to generate pseudo-control signals for tracking smooth reference trajectories. In addition, applications of generative adversarial networks and long- and short-term memory networks in AUV path planning and obstacle avoidance are discussed. Bao et al. [80] proposed an improved three-dimensional trajectory tracking control method based on SSA-RBF neural networks. They introduced the Chaotic Sparrow Search Algorithm (CSSA) to optimize the parameters of the neural network, enhancing its approximation ability to nonlinear systems and improving resistance to disturbances and tracking accuracy. When dealing with complex asymmetric saturation and unknown dynamics, Zhang et al. [81] proposed a neural network-based adaptive trajectory tracking control method. This method utilizes the nonlinear approximation ability of neural networks to handle unknown dynamics and disturbances in AUV systems and designs an adaptive law to dynamically adjust the neural network's weights to compensate for system uncertainties. However, neural network control typically faces challenges such as high training data requirements, high computational complexity, and insufficient interpretability.

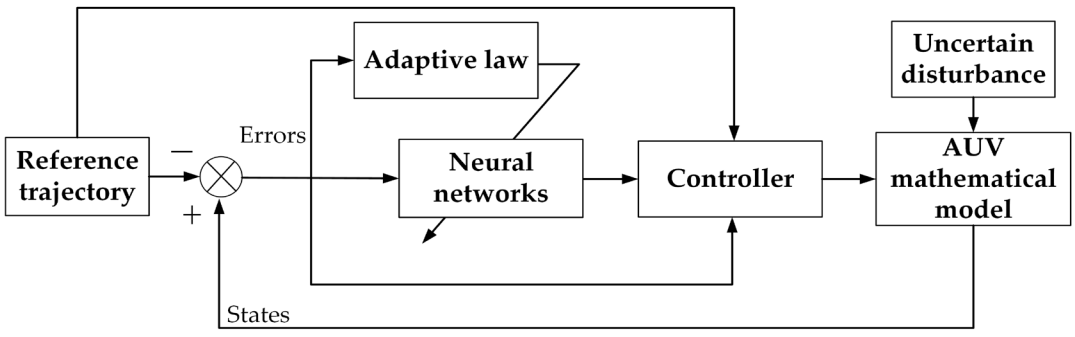


Figure 5. Block diagram of neural network control.

2.2.4. Adaptive Control

Adaptive systems enhance adaptability to uncertainties and disturbances by combining parameter estimation with disturbance compensation. Ma et al. [82] proposed a trajectory tracking controller design method based on robust adaptive control theory. This method suppresses uncertainty through a robust adaptive compensator and analyzes the stability of the closed-loop system using the Lyapunov method. The analysis demonstrates that the controller can maintain system stability and trajectory tracking accuracy under uncertainties and disturbances. This method emphasizes stability under uncertainty and disturbance and is suitable for longer trajectory tracking tasks. Based on traditional robust adaptive control, Hou et al. [58] designed an adaptive finite-time trajectory tracking controller. Here, the nominal controller tracks the desired trajectory, while the robust adaptive compensator adjusts parameters in real time to suppress uncertainties and disturbances. This method achieves faster convergence and stronger anti-interference capabilities, enabling trajectory tracking in a short time. It is suitable for scenarios requiring fast response.

This section examines key trajectory tracking strategies, including sliding-mode control, feedback linearization with MPC, neural network-based intelligent control, and adaptive control. These methods enhance robustness and accuracy under time-varying disturbances and nonlinear dynamics. However, their performance depends heavily on model accuracy and computational capacity, highlighting the need for lightweight and adaptive solutions.

To clarify the analysis and aid in understanding the trade-offs of different control methods, we pinpointed key features like applicability, robustness, and adaptability. Based on these, we carried out a comparative assessment of AUV control methods, with results shown in Table 5.

Table 5. Comparative evaluation of AUV control methods based on key features.

Control Methods	Robustness	Adaptability	Computational Cost	Implementation Simplicity	Practical Applicability
PID control	medium	low	low	high	good
sliding-model control	high	medium	medium	medium	good
model predictive control	high	high	high	low	medium
neural network control	medium	high	high	low	medium
reinforcement learning	medium	high	very high	low	emerging

2.3. Formation Control

Formation control refers to the coordination of multiple AUVs to maintain predefined relative positions and motion states during mission execution. This coordination realizes collaborative operations and improves mission execution efficiency and coverage. The schematic diagram of formation control is shown in Figure 6. The core objective of formation control is to ensure that multiple AUVs can accomplish their tasks in an orderly and efficient manner. It also enhances the robustness of the system so that the formation can maintain a stable structure and adapt to unexpected situations in a dynamic environment [83]. For the research of AUV formation control, existing methods mainly include leader–follower control, consensus control, virtual structure control, and behavior-based formation control. Each of these methods has its own characteristics and is applicable to different mission requirements and environmental constraints. The comparison of specific methods is shown in Table 6.

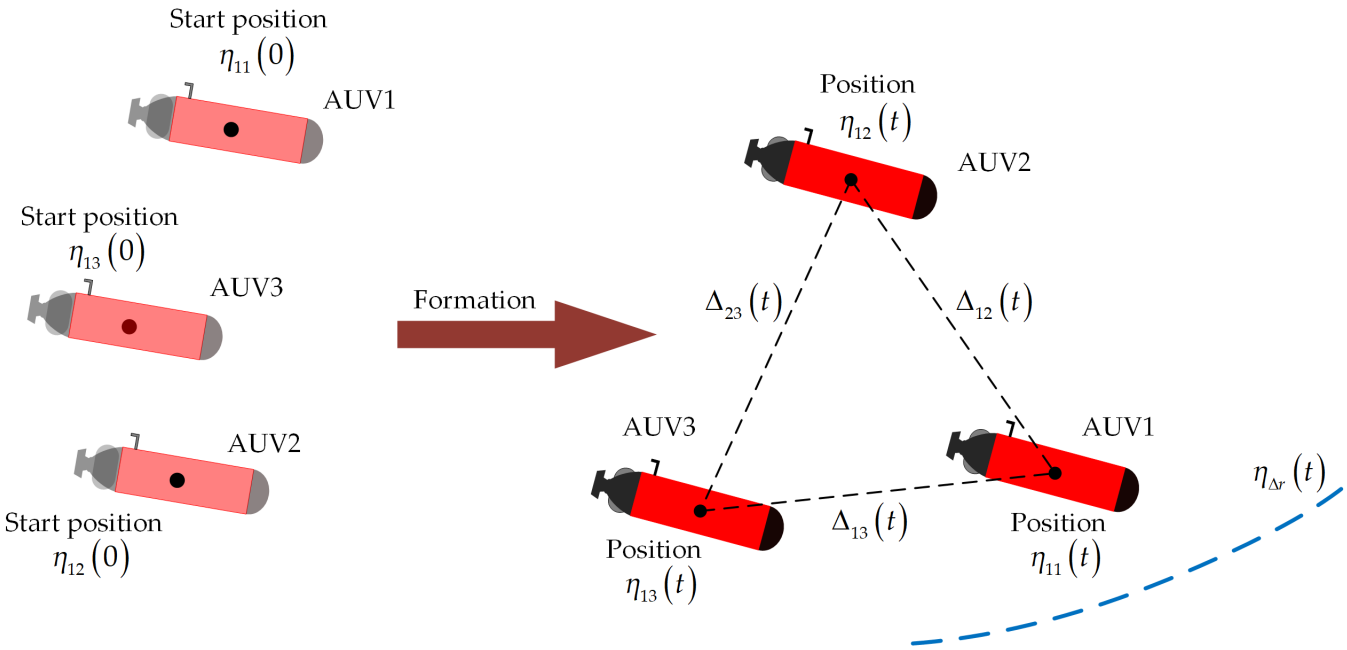


Figure 6. Diagram illustrating formation control for AUVs.

Table 6. Comparison of formation control methods.

Control Methods	Applicable Conditions	Advantages	Disadvantages
leader–follower method	cooperative operations of multiple AUVs, with a leader guiding the formation's movement	computational complexity [54], high control accuracy [84], reduced enhanced system robustness [85]	high communication demand [84], dependent on leader [86]
consistency control method	local interaction enables variable consistency	reduced dependence on global information [87,88], strong distributed autonomy [89], high robustness [90]	inadequate adaptation to dynamic environmental factors [89], face vibration issues [90]
virtual structure method	high-precision formations with high fault tolerance requirements	strong fault tolerance [91], high flexibility [40,92]	dependent on global information [40,91–94], high communication requirements [92]
behavior-based method	unstructured tasks with self-organized formations	high flexibility, adaptable to dynamic environments [95,96]	lack of global coordination [97], weak precise control ability [98,99]

2.3.1. Leader–Follower Method

The leader–follower method is a classical master–slave formation control strategy for multi-AUV cooperative operations. In this method, the leader AUV is responsible for guiding the formation's movement direction and speed, while the follower AUVs adjust their positions and speeds based on the leader's state information to maintain the preset formation structure. Cui et al. [84] developed a mathematical model for leader–follower formation control based on feedback linearization. This approach simplifies the complex dynamics model into a first-order system, thereby reducing control computational complexity. The control strategy maintains the formation structure by designing a control law that enables the follower AUVs to adjust their motion based on the leader's state information. However, this method relies on complete state information from the leader, which can pose high communication demands and potentially affect formation stability in cases of network instability or communication loss. To address these challenges, Cui et al. [85] proposed

a leader–follower control method that relies solely on the leader's position information. This method uses the leader's motion state and the desired formation shape to guide the followers' motion through a virtual navigator reference path. By avoiding the need for complete state information from the leader, this approach enhances system robustness. An adaptive variable-structure control law is employed to improve stability and anti-interference capabilities. Lyapunov stability theory is used to prove the closed-loop system stability. In recent years, researchers have focused on improving the leader–follower method to enhance formation control flexibility and robustness. Wang et al. [54] introduced a formation transformation control strategy based on a priority model. This strategy dynamically adjusts the formation by establishing a leader–follower model and introducing the priority of relative distance and angle. Compared to traditional methods, it effectively reduces computational complexity and maintains robustness in complex environments. Burlutskiy et al. [100] proposed an energy-efficient optimized formation control method based on a centralized leader–follower architecture. Their study realized the joint motion of AUVs and supporting vessels by developing a dynamics algorithm extended to multi-AUV formations. The study designed yaw, forward, and lateral control loops for AUVs and constructed a complex navigation system architecture to improve the realism and reliability of formation control. Additionally, the study considered the impact of the ocean environment on AUV motion, achieving improved coverage efficiency and communication quality while minimizing energy consumption through optimized formation configuration. Chen et al. [101] proposed a formation control algorithm combining consensus theory with the leader–follower approach. They designed a distributed control law that integrates consensus theory and leader–follower strategies. The proposed algorithm addresses the AUV formation problem under communication delay conditions. Simulation results demonstrate that the algorithm remains effective even with communication delays. Gao et al. [86] introduced an adaptive formation control method to address the formation control problem of underactuated AUVs with model uncertainty. This study offers a new perspective on applying the leader–follower approach to AUV formation control, particularly in handling model uncertainty and non-diagonalized system matrices. It enhances formation control robustness and provides theoretical support for practical applications.

While the leader–follower approach achieves high control accuracy in structured formations, it faces limitations due to communication dependency and potential leader failures. Therefore, developing compensation mechanisms for communication loss or network delay remains an important direction for future research.

2.3.2. Consistency Control Method

Consistency control is a distributed control strategy that aims to maintain a stable formation by converging the key variables (e.g., position, velocity, attitude, etc.) of multiple AUVs through local interactions. A block diagram of consistency control is shown in Figure 7. Zhen et al. [89] proposed a coherent control strategy based on graph theory, which enables individuals in a multi-AUV formation system to achieve synchronized motion without central control through local communication. Meanwhile, the researchers combined the gyro force obstacle avoidance method to enhance the formation stability and obstacle avoidance ability of AUVs in complex environments. Zhang et al. [87] proposed a consistency control algorithm containing relative position information and velocity dampers for multi-autonomous underwater vehicle systems containing communication delay, transformed the kinematics and dynamics models of AUVs into second-order integrator form by the feedback linearization method, and used Lyapunov generalization and linear matrix inequality theory to obtain the system to achieve sufficient conditions for consistency, and the simulation results verify the robustness and stability of the method

when randomly switching topology and formation transformations. Tao et al. [90] proposed a fixed-time distributed formation tracking control method, which employs adaptive backstepping sliding-mode control combined with a graph theory-based control protocol to ensure formation consistency. To reduce high-frequency jitter, the method introduces a bio-heuristic approach that uses a neural dynamic model to replace the nonlinear sign function or saturation function in conventional sliding-mode control, thereby improving robustness and reducing noise interference. Yu et al. [88] proposed an event-triggered consistency control protocol based on event triggering to reduce the occupation of communication resources, which combines the artificial potential field method with consistency control to solve the shortcomings of traditional control methods in obstacle avoidance. The design of the event-triggered conditions of this method may be complicated and requires precise parameter adjustment, otherwise it may affect the convergence performance and stability of the system. In practical applications, ref. [89] applied graph theory to the consistency control of a multi-AUV formation system to achieve synchronized motion among individuals through local communication without central control, which enhances the distributed autonomy and robustness of the system. However, it lacks the consideration of complex environmental factors common in practical applications, such as dynamic obstacles and time-varying communication topology. Ref. [87] proposed a coherent control algorithm containing relative position information and velocity dampers to realize formation consistency control under switching topology conditions. Although the communication delay is considered, the performance of the control algorithm may be affected in the case of large delay variations or high delay uncertainty, and further research on more robust delay handling methods is needed. Ref. [90] may still face the jitter problem when dealing with complex dynamics models, which affects the stability and control accuracy of the systems [88]. Although the occupation of communication resources is reduced, the event triggering mechanism may still need to be further optimized in practical applications to make more effective use of the limited communication resources.

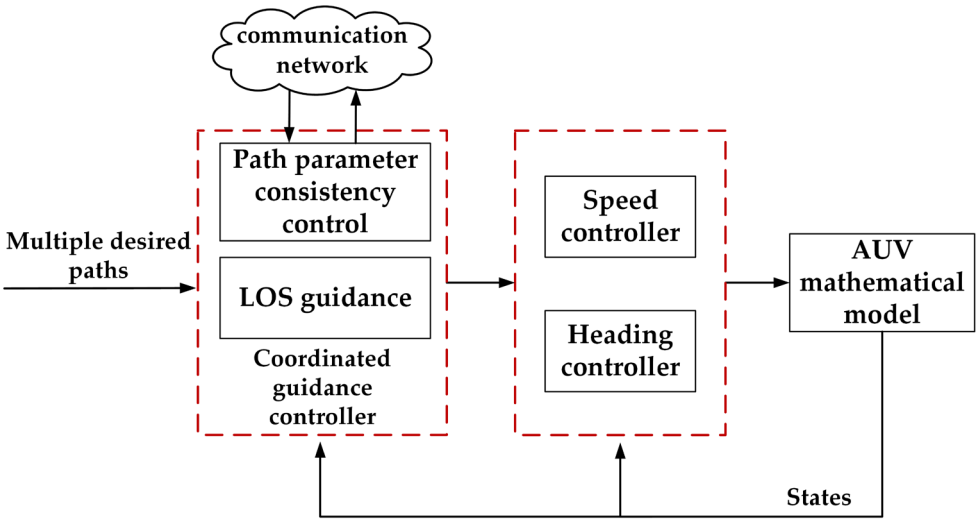


Figure 7. Block diagram of consistency control.

The advantage of consistency control is to reduce the dependence on global information and improve the distributed autonomy and robustness of the system. However, in dynamic formation tasks, the method still needs to be further optimized, especially in terms of dynamic task allocation and inter-individual communication mechanisms, in order to enhance the flexibility and adaptability of the formation. Future research can focus on multi-intelligent body cooperative optimization, intelligent task allocation, and control

strategies with low communication overhead to enhance the application capability of AUV formation systems in complex environments.

2.3.3. Virtual Structure Method

The virtual structure method treats the entire formation as a rigid structural body rather than as independent individuals. By defining a virtual geometric structure, it ensures that all AUVs maintain relative relationships, thereby realizing coordinated movement of the formation as a whole. Tan et al. [93] proposed a method based on minimizing a positional error function. Each AUV corresponds to a point in the virtual structure, and by optimizing the error function, the AUVs maintain the preset formation shape. M. Anthony Lewis et al. [91] applied the virtual structure method to high-precision formation control. Their study demonstrated that the method can maintain the integrity of the formation structure even when some AUVs fail, showing good fault tolerance. Atta et al. [94] designed virtual structures to achieve coordinated control among AUVs, enabling them to maintain the intended formation and perform their missions efficiently in underwater environments. Chen et al. [40] proposed a virtual structure-based fusion control strategy to achieve fast formation assembly, dynamic cooperative control, and autonomous obstacle avoidance. Compared to traditional formation control methods, this method does not rely on a single leader, reduces sensitivity to leader failure, and is more suitable for complex environments, allowing flexible adjustment of the formation structure. Zhen et al. [92] proposed a finite-time position and attitude tracking control method based on virtual structures and artificial potential fields. This method enables AUVs to quickly adjust their attitude during deployment and change formations after reaching a set depth. In [91,93], the virtual structure method does not require selecting a leader, avoiding the impact of leader failure on the entire formation. It provides better fault tolerance and the ability to adapt to multiple geometric formation structures. However, the method relies on precise global information and may be limited by communication constraints in long-distance or complex environments. Future work could combine this method with consistency control and intelligent optimization algorithms to improve flexibility and adaptability. The decentralized method in [91] may lead to less efficient coordination in large-scale formations and limited tolerance for communication delays and packet loss. Although ref. [40] combines techniques such as virtual structures and artificial potential fields, the local minima problem of the artificial potential field method in complex environments may cause AUVs to fall into a deadlock state. The control algorithm in [92] is more difficult to implement and requires higher sensor accuracy and communication bandwidth in practical applications.

The virtual structure method does not need to select a leader and avoids the effect of leader failure on the entire formation. It offers better fault tolerance and the ability to adapt to multiple geometric formation structures. However, it relies on precise global information and may be limited by communication constraints in long-distance or complex environments. Future work could combine this approach with consensus control and intelligent optimization algorithms to improve flexibility and adaptability.

2.3.4. Behavior-Based Method

Behavior-based formation control is a method to decompose the formation control task into multiple basic behaviors and realize the cooperative movement of multiple intelligences through behavior fusion. The core idea is to simulate the behavioral patterns of groups in nature and realize complex formation control tasks by defining and fusing multiple basic behaviors (e.g., obstacle avoidance, maintaining formation, following targets, etc.).

In the cooperative control of multiple AUVs, Li et al. [95] designed multiple behavioral modules by mimicking the behavior of moths and coordinated the priorities of different

behaviors through a hierarchical architecture. Wang et al. [96] proposed a path replanning algorithm combining dynamic and behavior-based behaviors for high-speed navigation and obstacle avoidance of underwater robots in complex environments. Xu et al. [102] provided a behavior-based solution for multi-AUV formation control, which improved the cooperative capability and stability of multi-AUV systems in complex underwater environments by optimizing the control algorithm and system design. Gan et al. [98] proposed a full-coverage confidence function path planning algorithm based on behavior strategies to optimize the path when the AUV navigates to the edge of an obstacle using specific behavioral strategies to avoid frequent dead zones. Balch et al. [99] proposed a behavioral control method that integrates formation behavior, obstacle avoidance behavior, and path planning behavior to enable AUVs to make autonomous decisions based on local sensing and communication for autonomous decision-making. However, this method does not fully consider the kinematics and dynamics of AUVs, which makes it difficult to ensure the stability of the global formation. Xu et al. [97] proposed a formation method based on local behavioral perception and self-organized control, which enables AUVs to autonomously adjust their motion strategies based on the surrounding environment and other individuals' behaviors through behavioral integration to achieve dynamic formation. However, due to its reliance on local information, the method may suffer from insufficient global coordination when coping with large-scale formation tasks. Behavioral control methods have the advantage of high flexibility for dynamic environments and unstructured tasks, but they still need to be improved in terms of precise control and overall coordination, and the feasibility of the system cannot be proved by good mathematics. The studies in [96,99,102] all focus on the cooperative control of multiple AUVs. While [96,102] implement multi-AUV formation control and target detection through behavioral strategies, ref. [99] further explores multi-AUV behavioral integration in navigation and obstacle avoidance. Together, these studies demonstrate the autonomy and synergy of multi-AUV systems in complex tasks. Refs. [98,99] use behavioral strategies to optimize the navigation performance of AUVs from the perspectives of path planning and formation control, respectively. Ref. [98] achieves full-coverage path planning through confidence functions and behavioral strategies, while ref. [99] achieves formation maintenance and navigation goal attainment for multiple AUVs through behavior control.

In summary, various formation control strategies—including leader–follower method, consistency control method, virtual structure method, and behavior-based method—demonstrate unique strengths and limitations under different mission scenarios and environmental constraints. While substantial progress has been made, many of these strategies face challenges in dynamic environments, particularly in communication reliability and coordination flexibility.

3. Analysis and Discussion

In this section, existing research results are analyzed and discussed, and future research directions are suggested.

After reviewing the major motion control strategies for AUVs, it is essential to examine the practical challenges that arise in real marine environments. In practical applications, AUV motion control still faces numerous challenges, primarily arising from the complexity of the marine environment and the inherent characteristics of AUV systems. This chapter focuses on the following key issues:

Environmental Adaptability: The uncertainties of the marine environment, such as ocean current variations, complex underwater terrain, and dynamic ocean conditions, remain major challenges for AUV motion control. Developing control strategies that can

effectively adapt to these unpredictable factors is crucial for improving the robustness and reliability of AUV operations.

System Characteristics: AUVs exhibit inherent nonlinear dynamics, multi-degree-of-freedom coupling, model uncertainties, and system constraints, all of which impose higher demands on control strategies. Addressing these issues requires advanced control techniques capable of handling complex dynamic interactions and uncertainties.

3.1. Impact of the Complex Environment on AUV Control

AUVs need to maintain stable operation in complex and changing marine environments when performing underwater missions. Factors such as ocean currents, water density gradient changes, and sea ice can affect the stability of AUV motion control [103–106]. Issues and challenges of AUVs in complex environments as summarized in Table 7.

Table 7. Environmental and operational challenges affecting AUV control.

Focus Problem	Path-Following Control	Trajectory Tracking Control	Formation Control	Main Methods and Techniques
environmental adaptability issues	current disturbances [65,107–111], water density stratification [112–114], sea ice (navigation failure) [115–118], waves (pose disturbance) [119–121]	current/wave disturbances [74,81], water density stratification [122]	current disturbances, sea ice [123–126], communication delays [127]	guidance law improvement [107–111,128–130], observer techniques [131–138], intelligent algorithms [117,118,139–142], sliding-mode control [25,65,119–121,133,143]
limitations of traditional methods	dependent on parameter assumptions [128,129], unmodeled dynamics leading to instability [144]	observation error hypothesis [25,138]	complex communication needs are hard to meet [145]	insufficient adaptability to environmental and system dynamics, relies on idealized assumptions
underwater communication problems	communication delays affect coordination [146,147]	acoustic noise interference [146]	low transmission rate and packet loss affect formations [127], sonar has a limited field of view [146]	disturbance rejection control [147], deep learning [127,146,147]

3.1.1. Effects of Currents

Currents are the main external factor affecting the trajectory of AUVs, and their uncertainty and randomness complicate path following and trajectory tracking. In environments with strong currents, not only does the trajectory of the AUV change, but energy consumption also increases. To cope with current disturbances, researchers have proposed several improved line-of-sight guidance methods, including the integral line-of-sight (ILOS) method, adaptive integral line-of-sight (AILOS) method, and adaptive line-of-sight (ALOS) method. These methods introduce different compensating mechanisms in the guidance law to eliminate the effect of currents on path following. In [107–109], an integral term is added to the classical LOS guidance law to mitigate the effect of unknown drift forces and improve the performance of path following. The unknown sideslip angle is regarded as a constant parameter in adaptive ILOS guidance and is estimated by an adaptive law that introduces a compensation inside the inverse tangent function [128,129,148]. These methods usually

work better when the sideslip angle is constant or varies a little. In [65,110,111], angle estimation is introduced outside the inverse tangent function, which can effectively deal with rapid angle changes caused by ocean currents. However, its performance may be somewhat limited when the sideslip angle changes are large. The block diagram of the path-following control based on the ALOS algorithm is shown in Figure 8. Some scholars have also adopted observation techniques to cope with current interference, such as by expanding the state observer to recognize the sideslip angle changes caused by currents and other disturbances [131,132,136]. This approach also has good estimation accuracy for larger sideslip angles but may result in a large overshooting phenomenon in terms of the tracking error.

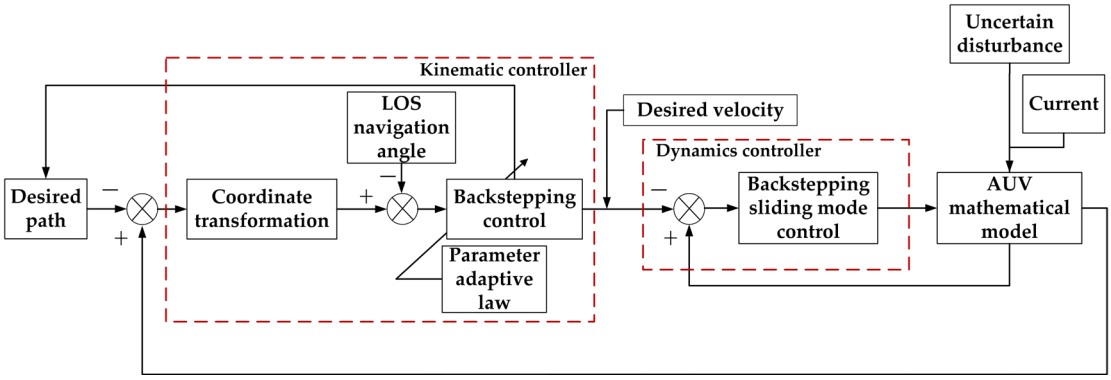


Figure 8. Block diagram of path-following control based on ALOS.

In addition, for the trajectory tracking and path-following problems of the navigator, researchers have designed a current observer to directly estimate the currents based on the kinematic model of the navigator [133–135]. He et al. designed the current observer to estimate the current velocity online and designed the sliding-mode control law to realize effective path-following control of the AUV under uncertainties such as currents and unknown disturbances [133]. The block diagram of the path-following control based on the current observer is shown in Figure 9. Many scholars have dealt with the problem of current disturbances in terms of planning. For example, Li et al. [11] proposed a bow acceleration planner based on optimal control, which improved the path tracking performance of AUVs in currents through the force vector synthesis method. Byunghyun Yoo et al. [140] and Hu et al. [149] optimized the path planning of AUVs in the presence of current disturbances using methods such as reinforcement learning. Wen et al. [139], Chen et al. [150], and Qu et al. [127] proposed efficient path planning strategies for different current conditions by building a 3D time-varying current model and improving the optimization algorithm, respectively. In multi-AUV systems, the dynamic influence of ocean currents makes the synergy among units more complicated. Bai et al. [123,124] proposed a cooperative path planning method based on dynamic partitioning and task allocation strategies, which utilizes a hybrid grid model and biological neural network technology to effectively cope with the uncertainty of ocean currents. This method improves the cooperative search and dynamic trajectory optimization capabilities.

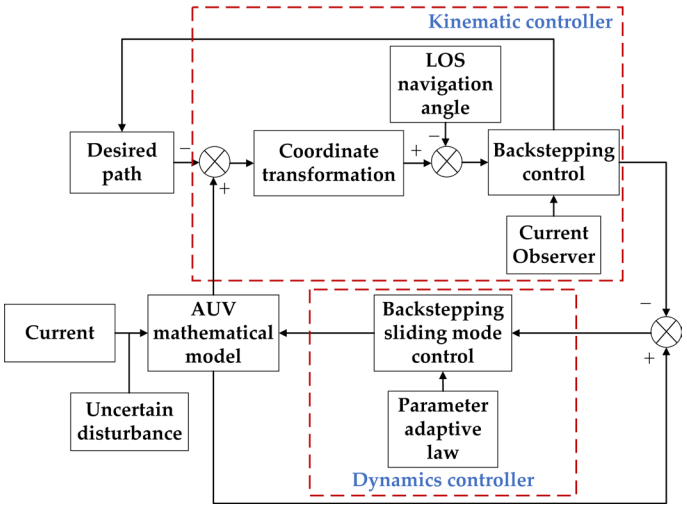


Figure 9. Block diagram of path-following control based on current observer.

3.1.2. Effects of Ocean Waves

When the AUV is navigating near the surface, waves can induce six-degree-of-freedom rocking motions, including pendulum, transverse rocking, and longitudinal rocking. These changes in motion attitude interfere with normal navigation, making it difficult to maintain a stable attitude and trajectory. To address wave interference, Su et al. [119] developed an integrated sway reduction control strategy for transverse and bow rocking. They used stochastic wave theory, adopted the ITTC two-parameter wave spectra to describe the waves, and established the motion model and wave interference model of the AUV. Using Morison's equations, they calculated the wave forces and moments acting on the AUV during near-surface dives. Simulations were conducted to analyze the AUV's transverse rocking motion during near-surface dives. A method to generate transverse rocking correcting moments using zero-speed deceleration fins was proposed, and a transverse rocking deceleration controller based on sliding-mode control was designed. Building on transverse rocking control, the bow rocking motion of the AUV was further analyzed, and a method to control the heading of the AUV by adjusting the rudder angle was proposed. An integrated controller for transverse and bow rocking was designed. Zhao et al. [120] investigated the impact of wave interference on the transverse rocking of AUVs. They simulated the wave interference force and moment under different sea conditions to obtain the interference characteristics of waves on the diving motion of underwater robots. They analyzed the working principle of horizontal rudder rocking reduction, which involves generating sufficient lift force by controlling the rotation angle and angular velocity of the horizontal rudder to counteract the wave-induced transverse rocking moment. A transverse rocking attitude controller based on variable structure control (VSC) theory was designed. By simulating the AUV transverse rocking control system based on the active flapping of the horizontal rudder, and comparing the simulation results with those without the rocking reduction control system, it was found that the rocking reduction effect was significant. Pan et al. [121] deduced the calculation formulas for first-order and second-order wave interference forces and moments. They analyzed in detail the impact of these forces on the pendulum motion of the AUV. Based on the principle of sliding-mode variable-structure control, they designed depth and longitudinal rocking angle controllers, achieving precise control of the AUV using the lifting force model of the horizontal rudder. Simulation results showed that the controller effectively reduced the impact of wave interference on the AUV and maintained stability under complex sea conditions.

3.1.3. Effects of Water Density Stratification

Seawater exhibits significant vertical stratification due to temperature, salinity, and pressure. This stratification affects AUV motion control in several ways. Vortices, internal waves, and turbulent wakes often form in stratified fluids. These complex flow phenomena alter local flow field characteristics, thereby impacting the navigational stability of AUVs. Wei et al. [112] and Cao et al. [113,114] investigated the wake structure and hydrodynamic characteristics under different stratified conditions using CFD simulations. Their research revealed how the vortex structure in the wake influences vehicle control. Additionally, water density stratification affects the propagation characteristics of underwater acoustic waves, reducing the localization accuracy of wireless sensing networks. Prateek et al. [122] proposed a sparse sensing-based acoustic localization method to address this issue. They established a stratified medium model to optimize signal propagation analysis.

3.1.4. Effects of Sea Ice

When operating in polar high-latitude waters, the dynamics and irregularities of sea ice pose significant challenges to the navigation and control of AUVs. In ice-covered areas, GPS signals are difficult to obtain, and sea ice interferes with acoustic signal propagation, seriously affecting navigation accuracy. Li et al. [115] and Zeng et al. [116] proposed a navigation and localization system for under-ice environments and an ice floe trajectory tracking method, respectively. These methods improve localization accuracy through multi-sensor fusion. The complexity of obstacle types in the sea ice environment and the dynamic changes in the ice cover make path planning more difficult. Zhong et al. [125] combined acoustic, inertial, and visual sensors to improve navigation accuracy using a multi-sensor fusion strategy. Shu et al. [126] quantified collision and entrapment risks by building a risk field model to provide decision support for path planning. Cao et al. [117] utilized deep learning techniques to detect obstacles in forward-looking sonar images and designed corresponding collision avoidance algorithms. These algorithms effectively improve obstacle avoidance performance in sea ice environments. To avoid the dynamic changes in ice cover and the high collision risk faced by AUVs when navigating in ice areas, Kevin Murrant et al. [118] proposed a dynamic path tracking method. This method uses a deep learning-based dynamic prediction model of ice areas to optimize path planning, ensuring the navigational safety of the ship in high-ice-concentration environments.

3.1.5. Other Factors

In practical applications, underwater acoustic communication faces many challenges, such as noise interference, low transmission rate, path loss, communication delay, and packet loss. These issues seriously affect the accuracy and cooperative performance of AUV formations. To cope with these challenges, Zhang et al. [127] proposed a pilot–follower formation system that adapts to communication delay. Assuming that the propagation delay is finite and smaller than the sampling period of the AUV, they enhanced the cooperative capability of the AUV formation in complex underwater environments by designing a controller to compensate for the effect of communication packet loss on the formation performance. They also introduced a terminal sliding-mode control technique to achieve fast convergence. To address the motion control problem of AUVs under random environmental disturbances, Peng et al. [151] investigated the trajectory tracking control of AUVs and the containment control problem of multiple AUVs. They proposed various control algorithms, including adaptive tracking controllers, distributed finite-time containment controllers, and distributed adaptive containment controllers. These algorithms effectively deal with the problems of random environmental disturbances, state constraints, and unknown speeds, improving the control performance and stability of AUVs in complex

marine environments. To address the three-bit trajectory tracking control problem of AUVs under environmental disturbances, Wu et al. [143] designed a backstepping sliding-mode controller based on a nonlinear disturbance observer (NDO). This controller introduces sliding-mode control based on traditional backstepping control and combines it with the NDO. The controller is designed by defining the tracking error, the virtual control volume, and the sliding-mode surface. The stability of the system is proved by the Lyapunov function, and the effectiveness and robustness of the method in AUV 3D trajectory tracking are verified by simulation.

Marine environmental factors such as ocean currents, waves, stratification, sea ice, and acoustic communication limitations pose significant challenges to AUV control. Control strategies must incorporate real-time adaptation, observer design, and predictive compensation to maintain stability and performance in these complex settings.

3.2. Impact of System Characteristics on AUV Control

AUV system characteristics are mainly reflected in the following three aspects: model uncertainty and external disturbances, coupling and nonlinear characteristics, and self-constraint characteristics. To address these problems, researchers have proposed solutions from various perspectives such as nonlinear control (e.g., sliding-mode control), intelligent control (e.g., neural networks), and observer design.

3.2.1. Model Uncertainty and External Disturbances

AUV systems often face parameter variations, structural uncertainties, and biases from model simplifications in real-world operation. Traditional control methods have limitations in adapting to time-varying disturbances. Qiao et al. [152] used adaptive integral terminal sliding-mode control, which utilizes an adaptive mechanism to estimate the upper bound of system uncertainty, thus reducing the impact of model bias on control performance. Although adaptive control can handle parameter uncertainty, it becomes unstable in the presence of unmodeled dynamics. F. Muñoz et al. [144] proposed an adaptive control strategy using a dynamic neural network to compensate for model uncertainty by adjusting the network weights online. Wang et al. [153] used a radial basis function (RBF) neural network for estimating and compensating for model uncertainty and optimized it based on the sliding-mode control approach, which improved the robustness of the system. Yan et al. [154] proposed an asynchronous localization algorithm based on reinforcement learning for online adjustment of time-varying uncertain model parameters, which effectively improves the localization and control performance of the system under uncertainty conditions. Neural networks and fuzzy logic systems are often used to approximate nonlinear parameters, which can improve the robustness of controllers to uncertainty, although it is difficult to achieve complete freedom from parameter dependence. Patre et al. [155] built a fuzzy terminal sliding-mode controller and integrated fuzzy logic into the control system for compensating for unmodeled dynamics, external disturbances, and time-varying parameters, which enhanced the robustness of the control strategy. Nonetheless, the complexity of parameter tuning remains a limiting factor for the application of fuzzy control techniques in motion control. Zhang et al. [156] proposed a conversion error control strategy without the need to know the model parameters by means of fast dynamic compensation, which improved the system robustness. In addition, some scholars have also estimated the centralized perturbation by designing a perturbation observer. Gao et al. [137] designed a backstepping control scheme based on a perturbation observer for trajectory tracking control under parameter uncertainty and external environmental perturbations. Rong [138] designed a fractional-order sliding-mode perturbation observer, which provides an effective estimation of random perturbations in the environment and adopts a sliding-mode

control strategy, which guarantees the tracking accuracy. Considering the upper limit of the observation error of the observer as a constant may affect the dynamic performance of the system when there is a large change in the external disturbance. He et al. [25] introduced an adaptive mechanism in the design of the observer, which can better adapt to changes in the external environment by estimating the upper limit of the observation error online. In terms of formation control, Liu et al. [145] proposed a distributed control protocol based on relative position and velocity without complex communication. By optimizing the performance function and control gain, the method is able to maintain system robustness under external disturbances and model uncertainties, while avoiding collisions and achieving relative positioning of AUVs. Xia et al. [157] improved the stability of the system through singular perturbation methods and robust design, solved the formation control problem of AUVs under uncertainty conditions, and simplified the control design process. Jin et al. [158] proposed a distributed event-driven formation control strategy to solve the formation control problem under networked uncertainty. Xu et al. [159] designed an extended state observer and combined it with individual fault values provided by a fault estimation observer to study the multi-AUV 3D formation control problem. Cui et al. [160] designed an extended state observer for real-time estimation of internal uncertainties and external disturbances, integrated the potential function into the designed formation control strategy to avoid collisions, and effectively solved the formation control problem of multi-AUV systems under actuator saturation and external disturbance conditions.

3.2.2. Coupling and Nonlinear Characteristics

AUVs typically exhibit highly nonlinear and multi-degree-of-freedom coupled dynamics. To address the challenges posed by complex dynamics and nonlinearities, researchers have proposed various strategies: Khoshnam Shojaei et al. [161] designed a nonlinear saturated observer and a saturated tracking controller, enabling three-dimensional trajectory tracking of AUVs in the absence of velocity sensors. Lionel Lapierre et al. [162] developed a nonlinear path-following controller based on backstepping and Lyapunov stability theory, ensuring stable tracking of predefined paths. Similarly, Jia et al. [163] employed backstepping to design a nonlinear controller and introduced a disturbance observer to compensate for composite uncertainty disturbances, demonstrating strong robustness in 3D path following. Additionally, Shen et al. [164] proposed a model predictive control framework based on Lyapunov theory, incorporating contraction constraints through a nonlinear backstepping tracking control law to enhance trajectory tracking performance. Manish Sharma et al. [165] addressed actuator-induced nonlinearities by constructing a reduced-order observer using a wavelet neural network to compensate for system uncertainties. For large-scale dynamically coupled nonlinear systems, Cui et al. [166] introduced an adaptive sliding-mode control method to effectively manage input nonlinearities and positional disturbances in AUV attitude control. Meanwhile, Dunbar et al. [167] developed a distributed backward time-domain control algorithm for trajectory tracking in dynamically coupled nonlinear systems. This approach not only improves system stability and performance but also reduces the computational burden associated with centralized control.

3.2.3. Constraint Properties

The motion control of AUVs often encounters multiple physical and operational constraints, which not only limit the vehicle's degrees of freedom but also impose higher requirements on control strategies. To address these challenges, researchers have explored robust, adaptive, and MPC methods to develop efficient control schemes under such constraints. Li et al. [168] proposed a simple adaptive trajectory tracking control scheme to handle the control problem of underactuated AUVs under unknown dynamics and LOS

constraints. Zhang et al. [169] designed a three-dimensional trajectory tracking controller based on MPC, ensuring high control accuracy while accounting for practical constraints such as actuator saturation. Similarly, Shen et al. [164] introduced a Lyapunov-based model predictive control (LMPC) framework for AUV trajectory tracking, which explicitly considers actuator saturation and incorporates contraction constraints to enhance trajectory tracking performance in complex environments. To address actuator saturation in controller design, Pouria Sarhadi et al. [170] proposed a model-referenced adaptive PID control method incorporating a dynamic anti-saturation compensator. By integrating an adaptive PID controller with modern anti-saturation techniques, this approach effectively mitigates the impact of actuator saturation. In the domain of formation control, Wei et al. [171] developed a distributed Lyapunov-based MPC method to improve multi-AUV formation tracking performance by considering actuator saturation and state constraints through online optimization techniques. Yan et al. [172] designed an observer for each AUV to estimate the overall system state, effectively addressing the trajectory tracking problem in multi-AUV systems with actuator saturation by optimizing control inputs and local information exchange. Du et al. [173] tackled input saturation issues by integrating active communication delay compensation, a data-driven state predictor, and a neural network. They employed a backstepping-based auxiliary dynamic system to mitigate the negative effects of input saturation. Additionally, they used Lyapunov-based stability constraints to ensure that the multi-AUV system maintains the desired three-dimensional time-varying formation pattern while achieving asymptotic stability of formation errors and satisfying performance constraints.

In summary, several research problems and challenges remain inadequately addressed, thus necessitating further investigation into this topic.

3.3. Future Research Directions

Despite significant advancements in AUV motion control technologies, particularly in addressing nonlinear coupling, model uncertainties, and various constraints, traditional control methods and emerging techniques such as deep reinforcement learning still face limitations. These challenges are especially pronounced in highly dynamic and extreme marine environments, where adaptability and robustness remain critical concerns. Future research should focus on integrating advanced strategies such as disturbance rejection, adaptive control, prescribed performance control, and distributed coordination to develop more intelligent, efficient, and robust AUV motion control systems. These advancements will be essential in meeting the increasing demands of marine resource exploration, environmental monitoring, and military reconnaissance, where precision, real-time performance, and collaborative capabilities are paramount. Based on an in-depth analysis of existing studies, the following key research directions are proposed:

1. Enhancing Intelligent Control and Autonomous Decision-Making

The future development trend of AUV control system lies in realizing a higher level of intelligence and autonomous decision-making capability. With the continuous maturation of artificial intelligence and deep learning technologies, the focus should be on exploring the combination of reinforcement learning, fuzzy control and neural network methods, so that the AUV can learn autonomously, dynamically adjust its tasks, and realize a seamless transition from local perception to global decision-making. Developing self-correcting navigation algorithms based on real-time data feedback and using deep neural networks for online estimation of the environmental state will thus realize rapid adjustment of trajectory and attitude, reducing the dependence on accurate mathematical models. It is vital to study the intelligent obstacle avoidance mechanism that integrates sensor data and environment modeling, and realize the AUV to autonomously plan safe and efficient

paths in complex marine environments through reinforcement learning and nonlinear optimization algorithms.

2. High-Precision Navigation and Multi-Sensor Fusion

Deep Integration of Multiple Navigation Techniques: There is potential in combining inertial navigation systems (INSs), acoustic positioning, and visual SLAM through advanced filtering algorithms and AI-driven techniques to achieve real-time error compensation, alongside real-time updates and compensation for sensor drift and accumulated errors to ensure long-term navigation stability and reliability, particularly in GNSS-denied environments.

Distributed Cooperative Navigation: We can leverage inter-AUV information sharing to establish a distributed navigation framework, where individual AUVs enhance overall navigation accuracy through complementary localization data—especially crucial for deep-sea and extreme environments.

3. Multi-AUV Cooperative Operations and Distributed Control Optimization

A single AUV is limited by energy and load capacity, and multi-AUV cooperative operation is an inevitable trend to realize large-scale ocean missions. The future should focus on distributed task allocation and cooperative control based on game theory and distributed optimization theory, designing efficient task allocation algorithms that allow each AUV to make autonomous decisions under local communication conditions and achieve coherence of global objectives. A hybrid formation control strategy may involve exploring the hybrid strategy of leader–follower, consistency control and virtual structure control, which reduces the dependence on a single node or global information and improves the flexibility and fault tolerance of the formation by integrating their respective advantages. We can develop multi-AUV cooperative obstacle avoidance and path planning algorithms by utilizing real-time environment sensing and deep reinforcement learning to ensure that each airframe can safely and efficiently perform tasks under dynamic obstacles and complex flow field conditions.

Future research in AUV motion control will increasingly focus on the deep integration of interdisciplinary technologies and systematic design. By incorporating advanced intelligent algorithms, distributed coordination mechanisms, high-precision navigation, and energy management techniques, the goal is to establish a fully autonomous, highly robust, and efficient control system tailored for complex and dynamic marine environments. These advancements will significantly enhance AUV capabilities in oceanographic research, resource exploration, and national defense applications, while also laying the foundation for the next generation of intelligent marine equipment.

4. Conclusions

This paper systematically reviews the strategies for AUV path following, trajectory tracking, and formation control. It begins with an analysis and summary of classical control methods (e.g., PID control, sliding-mode control, model predictive control) and intelligent control strategies (e.g., fuzzy logic control, neural network control, reinforcement learning), focusing on their advantages, limitations, and practical applications. It also explores recent advances in multi-AUV coordinated operations, including leader–follower, consistency control, virtual structure control, and behavior-based control methods. On this basis, the existing research results are analyzed and discussed, and the advantages and limitations of various control methods in enhancing system robustness against external disturbances, system nonlinearities, model uncertainties, and physical constraints are evaluated. Future research should focus on enhancing the robustness of control systems, optimizing multi-sensor data fusion, leveraging artificial intelligence to improve adaptive decision-making

capabilities, and refining the coordinated control strategies for AUV formations. It is hoped that this review will provide valuable references and ideas for researchers in this field.

Author Contributions: Conceptualization, L.H.; resources, Y.Z.; writing—original draft preparation, M.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Armament and Equipment Advance Research Project of the Central Military Commission, grant number 90903010102.

Data Availability Statement: Data are contained within the article.

Acknowledgments: The authors would like to express their sincere gratitude to the reviewers for their valuable time and professionalism. The reviewers' critical comments and suggestions for improvement played a key role in enhancing the quality and completeness of this paper, enabling this study to be presented to a wider audience in a more rigorous form.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Glossary of Terms

1. AUV (autonomous underwater vehicle): A self-guided unmanned vehicle that operates underwater without real-time human control.
2. Path following: Control strategy guiding the AUV along a predefined geometric path without explicit timing constraints.
3. Trajectory tracking: Control strategy ensuring the AUV follows a time-dependent spatial trajectory.
4. Formation control: Techniques to coordinate multiple AUVs to maintain relative positioning during cooperative missions.
5. PID (proportional–integral–derivative) control: A classical feedback controller widely used for its simplicity and reliability.
6. Sliding-mode control (SMC): A nonlinear robust control strategy known for its strong disturbance rejection.
7. Model predictive control (MPC): An optimization-based control strategy that uses a model to predict and optimize future system behavior.
8. Reinforcement learning (RL): A type of machine learning where agents learn optimal policies through interactions with the environment.
9. Fuzzy logic control: A rule-based control method that handles uncertainty and imprecision using fuzzy set theory.
10. Adaptive control: A control method that adjusts controller parameters in real time to cope with system uncertainties.
11. Consistency control: A distributed control method that ensures multiple agents agree on certain variables through local interactions.
12. Virtual structure: A formation control method treating all vehicles as rigidly connected parts of a single virtual object.
13. Underactuated system: A system with fewer control inputs than degrees of freedom, common in AUV design.
14. Observer: A computational tool to estimate unmeasurable internal states or disturbances in a control system.

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