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Abstract

Extra-large autonomous underwater vehicles (XLAUVs) face multimodal detection threats involving acoustics, magnetic fields, electromagnetics, and hydrodynamic wakes in complex adversarial environments. Their detectability exhibits cross-domain coupling and multiscale interweaving, while existing research still lacks a systematic theoretical framework and technical support for the coordinated control of energy consumption, maneuverability, and stealth. This paper systematically reviews key technological advances in low-detectability navigation for XLAUVs. First, multidomain detectability mechanisms and signature prediction methods are summarized, and their modeling characteristics in trajectory planning and control are analyzed. Second, the algorithmic principles and applicable scenarios of five mainstream low-detectability trajectory planning methods are compared, namely offline optimization, model predictive control, graph search, game theory, and reinforcement learning. Furthermore, the influence mechanisms of control inputs on source level, wake characteristics, and structural vibration are discussed, and an analysis is introduced of the suppression effect of superhydrophobic drag reduction technology on the "friction–vibration–sound" pathway. The study shows that existing planning methods perform well in static environments, but lack real-time capability and robustness in dynamic, uncertain adversarial scenarios. At the control level, hierarchical control architectures outperform single feedback control in stealth missions, while superhydrophobic surfaces can simultaneously reduce drag and radiated noise, achieving coordinated optimization of energy consumption and stealth. On this basis, a five-layer integrated covert navigation framework encompassing "materials–dynamics–detectability–planning–control" is constructed. This paper identifies three key scientific issues: multidomain coupled modeling, online signature prediction, and multi-platform cooperative stealth, and points out that integrating data-driven modeling with physical mechanisms is an effective path to overcoming these bottlenecks. This review can provide a systematic reference for the overall design, algorithm selection, and engineering deployment of next-generation low-detectability XLAUVs.

Full Text

Research on Low-Detectability Trajectory-Tracking Control Methods for XLUUV Based on Wall-Slip Effects

Abstract: In complex adversarial environments, extra-large autonomous underwater vehicles (XLAUVs) face multimodal detection threats such as acoustics, magnetic fields, electromagnetics, and fluid wakes. Their detectability exhibits cross-domain coupling and multiscale intertwined characteristics, while existing studies still lack a systematic theoretical framework and technical support for coordinated control of energy consumption, maneuverability, and stealth (objective). This paper systematically reviews key technological progress in low-detectability navigation for XLAUVs. First, multi-domain detectability mechanisms and signature prediction methods are sorted out, and their modeling characteristics in trajectory planning and control are analyzed. Second, the algorithmic principles and applicable scenarios of five mainstream low-detectability trajectory-planning methods—offline optimization, model predictive control, graph search, game theory, and reinforcement learning—are compared. Furthermore, the mechanisms by which control inputs affect acoustic source levels, wake characteristics, and structural vibration are discussed, and superhydrophobic drag-reduction technology is introduced to analyze its suppressive effect on the "friction–vibration–sound" chain (method). Studies show that existing planning methods perform well in static environments, but their real-time performance and robustness are insufficient in dynamically uncertain adversarial scenarios. At the control level, hierarchical control systems are superior to single feedback control in stealth missions, while superhydrophobic surfaces can simultaneously reduce drag and radiated noise, thereby achieving coordinated optimization of energy consumption and stealth. On this basis, a five-layer integrated stealth-navigation framework of "material–dynamics–detectability–planning–control" is constructed (results). This paper summarizes three key scientific issues: multi-domain coupled modeling, online signature prediction, and multi-platform cooperative stealth, and points out that data-driven modeling combined with physical mechanisms is an effective path for breaking through the above bottlenecks. This review can provide systematic reference for the overall design, algorithm selection, and engineering deployment of a new generation of low-detectability XLAUVs (conclusion).

Keywords: extra-large unmanned underwater platform; stealth trajectory planning; robust tracking control; superhydrophobic drag reduction; adaptive intelligent decision-making

1. Introduction

In recent years, with the rapid development of autonomous navigation technology, the endurance, payload, and automation capabilities of a new generation of autonomous underwater vehicles (AUVs) have been continuously improved, gradually becoming an effective supplement to traditional manned submarines. Extra-large unmanned underwater platforms with diameters exceeding 2133 mm and cross-ocean navigation capabilities (extra-large AUV, XLAUV) are gradually becoming an important direction in the development of international naval equipment[^1,^2]. For example, the "Orca" and "Echo Voyager" of the United States[^3,^4], Russia's "Poseidon"and "Harpsichord"[^5,^6], Italy's "MGL20/ER" [^7], as well as China's HSU-001, HSU-100, and AJX-002 XLAUVs, all show that large AUVs are moving from the prototype verification stage toward the stage of systematic equipment. Their mission scope covers stealth reconnaissance, intelligence collection, deployment of sensor arrays, and deep-sea penetration in denied environments.

Against this background, advancing in parallel with the rapid evolution of equipment technology is the multimodal and multi-domain integration trend of counter-submersible detection systems. Over the past decade, numerous studies have shown that modern anti-submersible systems have expanded from traditional passive and active sonar[^8,^9,^10] to magnetic anomaly[^11], underwater weak electric fields[^12], electromagnetic leakage[^13], infrared imaging[^14], satellite synthetic aperture radar (SAR)[^15], wake identification[^16], and multi-source observation fusion[^17]. Especially for massive XLAUVs, their propulsion noise, structural vibration, thermal wakes, vortex-feature scales, and magnetic anomaly amplitudes are all significantly higher than those of small and medium-sized AUVs, making them still likely to be captured under long-distance, high-background-noise conditions, thereby posing a direct threat to mission survivability[^18].

In response to the above challenges, research in recent years has mainly focused on three technical directions:

(1) **Multi-domain detectability modeling.** Modeling methods for acoustic propagation, flow-induced noise, wake vortices, magnetic induction, electric-field leakage, and thermal/optical anomalies have been studied in depth in multiple fields[^19–^22]. However, most models are dominated by physical simulation or acoustics/fluid specialties and lack lightweight, state-dependent representations that can be directly embedded into trajectory-planning and control systems. Especially on larger-scale platforms such as XLAUVs, detectability signatures show stronger time variability and cross-domain coupling, but there is currently no mature system-level unified framework.

(2) **Stealth trajectory planning and adversarial strategy generation.** In recent years, methods such as model predictive control (MPC), stochastic optimization, Bayesian games, reinforcement learning, and deep reinforcement learning have gradually been introduced into AUV planning and detection-avoidance fields, and progress has been made in local environmental avoidance, sonar-dominant evasion, and energy-constrained planning[^23–^27]. However, most existing studies are based on single-domain acoustic models or simplified detector assumptions, and lack systematic methods for "uniformly embedding" multi-domain risks such as acoustic, magnetic, electric, and wake signatures into planning cost functions. At the same time, there is a lack of detectability surrogate models suitable for nonlinear and large-inertia platforms such as XLAUVs, making it difficult to use true detectability evaluation in real-time planning.

(3) **Stealth navigation control and enhancement of system robustness.** In the field of AUV control, extensive research has been carried out around robust H_∞ control, higher-order sliding modes, disturbance rejection control, and deep-reinforcement-learning-assisted control[^28–^32]. However, these methods are mainly aimed at disturbance suppression and tracking-accuracy improvement, with few coupled control strategies

specifically addressing the relationship among the "control-input spectrum–source level/wake disturbance–detectability." In other words, there remains a lack of linkage between control theory and the physical mechanisms of detectability. For large platforms, changes in attitude and velocity induce larger vortex scales, propulsor excitation, and structural vibration; therefore, detectability metrics need to be directly incorporated into control-law design, but current research is still in the early exploratory stage.

At the same time, related research in the field of materials engineering (such as superlubricating coatings, low-friction surfaces, microtextures, and ionic-liquid lubrication) has achieved breakthroughs in reducing mechanical friction noise, suppressing structural vibration, and improving propulsion efficiency[^33-37], and has demonstrated significant performance in gears, bearings, and sealing systems. Although the existing literature has shown the suppressive effect of superlubrication technology on the friction–vibration–acoustic chain[^33,^38,^39], its systematic coupling with AUV dynamics, energy-consumption models, and observability models remains lacking, and a unified analytical path of "materials–dynamics–stealth performance–planning/control" has not yet been formed.

In summary, the current research system has the following key gaps: there is still no unified multi-domain observability framework covering acoustics, optics, magnetism, electricity, and wake disturbances, and there is a lack of lightweight mathematical forms that can be directly embedded into planning and control. There is a shortage of observability proxy models applicable to XLAUVs, making it difficult to obtain reliable signature evaluation for real-time low-observability trajectory planning (low-observability trajectory planning, LOTP) and online control. Cross-scale coupling research on "materials–dynamics–stealth–control" is extremely scarce, making it difficult to systematically assess the system-level impact of superlubrication technology on stealth capability. Most existing planning and control methods do not explicitly consider observability indices and their spectral characteristics, making it difficult to satisfy concealment requirements of large-scale platforms in adversarial detection environments.

Based on the above background and research gaps, this paper aims to systematically review, for the stealth navigation requirements of XLAUVs, multi-domain observability mechanisms, observability modeling methods, stealth trajectory-planning strategies, stealth navigation control methods, and engineering applications of superlubrication technology; and to construct an integrated technical framework running through "physical characteristics–modeling–planning–control–materials," thereby providing a technical foundation and research directions for the design, optimization, and deployment of future low-observability autonomous underwater platforms.

2. Observability Mechanisms of XLAUVs

Stealth is a core indicator of whether an XLAUV can perform long-duration reconnaissance, penetration, and surveillance missions in adversarial maritime environments. Because of their large size, high propulsion power, and strong dynamic coupling, their radiative characteristics are much stronger than those of small and medium-sized AUVs, giving them a higher probability of being detected in multiple domains such as acoustics, non-acoustics, and hydrodynamic disturbances. At present, certain achievements have been made in source-level modeling, magnetic-anomaly analysis, electric-field and electromagnetic-leakage prediction, thermal/optical wake modeling, and turbulent-wake identification, and a relatively mature multi-domain detection-model system has been formed. This chapter aims to systematically sort out and integrate these studies, providing a unified observability framework for subsequent planning and control models.

2.1 Acoustic Signature

The acoustic exposure of XLAUVs mainly comes from structural-vibration noise, propulsion noise, and flow-induced noise generated by high-speed navigation. Among them, structural-vibration noise is produced by periodic loads in the propulsion system, pump-valve actuators, and energy systems (including fuel cells, lithium batteries, and diesel generators), and its spectrum exhibits significant discrete-line spectral characteristics. Such noise is radiated into the water through the hull, forming the platform' s inherent radiated-noise spectrum $S_L(f; x, u)$, where f is the given frequency, x is the state variable containing position, attitude, and load, and u is the corresponding control input containing the speed U, rudder angle δ, and propulsion speed n.

Propellers and pump-jet propulsion devices generate blade-frequency and harmonic-frequency components at high rotational speeds; when the cavitation number is below the threshold, cavitation bubbles collapse and form strong broadband noise, which is the most dangerous exposure source. For this part of the noise source, Zhu Manfu et al. have already conducted a detailed analysis in the literature[^37]. Propulsor noise usually increases nonlinearly with propulsion speed n, and can be approximated as $S_L \propto n^3 - n^4$. During high-speed navigation, the turbulent boundary layer and wake cause pressure pulsations input to the sensors, producing a typical $f^{-5/3}$ turbulent energy-spectrum decay. When the speed exceeds 3 kn–4 kn, flow-induced noise becomes the dominant noise source.

Considering that underwater sound propagation follows the relationship of "source level-propagation-noise-directivity," therefore, at a given frequency f, the engineering source-level model—that is, the XLAUV radiated sound level $S_L(f; x, u)$—can be decomposed into the form of a base spectrum plus state-dependent increments:

$$S_L(f;x,u) = S_{L0}(f) + \Delta_U(f,U) + \Delta_\delta(f,\delta) + \Delta_n(f,n) + \varepsilon_{struct}(f,\eta)$$

where $S_{L0}(f)$ denotes the baseline sound spectrum under the no-load, stationary, and no-rudder-deflection static condition; $\Delta_U(f,U) = a(f)U^{p(f)}$ denotes the increment related to speed, $a(f)$ is the frequency-dependent coefficient, and $p(f) \in [2,4]$ is an empirical exponent, usually taken as 3; $\Delta_\delta(f,\delta) = b(f)|\delta|^q$ denotes the increment related to rudder angle or attitude, $b(f)$ is the frequency-dependent coefficient, and the exponent $q \in (1,2)$. If the noise is linearly related to the rudder angle, one may set $q \approx 1$; otherwise, $q \approx 2$. $\Delta_n(f,n) = c(f)n^r$ denotes the increment related to propulsion speed, where $c(f)$ is the frequency-dependent coefficient, and $r \in (3,4)$ is an empirical exponent associated with the strong nonlinear growth of noise as the rotational speed increases; $\varepsilon_{struct}(f,\eta) = \sum_i g_i(f)h_i(\eta) + \xi(f,t)$ characterizes nonstationary or nonlinear structural noise that is difficult to explain directly using a single control variable, where $g_i(f)$ is the structural modal shape, $h_i(\eta)$ is an amplitude factor varying with health parameters, and $\xi(f,t)$ is a time-dependent random disturbance.

The loss during noise propagation can be represented by a hybrid model of "geometric spreading + absorption" [^39], with the specific expression as follows:

$$T_L(f,R) = 20log_{10}R + \alpha_{abs}(f)R + TL_{geo\_mod}(f,R)$$

where $\alpha_{abs}(f)$ is the frequency-dependent acoustic absorption coefficient, R is the propagation distance, and $TL_{geo\_mod}(f,R)$ may include multipath/seabed-reflection corrections.

The background noise

$$N_L(f) = NL_0(f) + 10\log_{10}(1 + W^\beta)$$

can be represented by the *Wenz* curves or wave-shipping empirical models, where W is the wind speed or an index of near-sea human-activity intensity. The receiving-array gain is denoted by $D_I(f)$. Therefore, engineering

The model formula describes the received signal-to-noise ratio:

$$SNR(f;x,u,R) = S_L(f;x,u) - T_L(f,R) - [N_L(f) - D_I(f)]$$

If SNR is integrated over the frequency band B, the bandwidth is obtained as $SNR_B = 10\log_{10}\left(\int_B 10^{\frac{SNR(f)}{10}} df\right)$. Based on the energy-detection approximation, the detection probability P_d can be described by a Gaussian approximation: $P_d \approx 1 - \Phi\left(\frac{\gamma - SNR_B}{\sigma_{SNR}}\right)$, where γ is the detection threshold (dB), Φ is the standard normal CDF, and σ_{SNR} denotes the statistical fluctuation of SNR (environmental fluctuation/modeling error).

Figure 1. XLAUV acoustic-signature framework diagram

Figure 1: Figure 1. XLAUV acoustic-signature framework diagram

Hard constraint [40]: ensure that the entire trajectory $x(t)$, $u(t)$ satisfies $SNR_B(x(t), u(t), R_{sensor}) \leq SNR_{th}$ (or $P_d \leq P_{d,th}$).

Soft constraint (penalty term): add an acoustic-exposure penalty to the trajectory cost,

$$J = \int_0^T \lambda_a SNR_B(x(t), u(t)) + \lambda_e E(u(t))dt,$$

where $E(u)$ is the energy-consumption model, and λ_a and λ_e are weights.

Figure 1. XLAUV acoustic-signature framework diagram

2.2 Non-acoustic signatures

With the multimodal development of anti-submarine technologies, non-acoustic detection methods play an increasingly prominent role in shallow seas and complex environments. Typical non-acoustic signatures include magnetic anomalies, electric-field and electromagnetic leakage, thermal wakes, and optical disturbances. These features have higher exposure in shallow seas, high-conductivity waters, and regions with significant background temperature gradients, and are key constraints in the stealth design of large platforms.

(1) Magnetic-anomaly signature

Magnetic-anomaly detection is widely applied in low-altitude patrol aircraft, buoy, and towed-array systems [41,42]. Its detection range can reach hundreds of meters to several kilometers, and it is especially more sensitive to magnetic levels for ultra-large mobile platforms such as XLAUVs. The platform magnetic signature is jointly composed of permanent magnetization and induced magnetization; thus the total magnetic moment of the platform can be written as

$$m(x) = m_p + m_i = m_p + \mathcal{K}(x)H_{earth}(x),$$

where m_p is the permanent magnetic moment, m_i is the magnetic moment induced by the geomagnetic field $H_{earth}(x)$, and $\mathcal{K}(x)$ is the position/load-related susceptibility coefficient matrix.

(2) Underwater electric-field and electromagnetic-leakage signature

Electromagnetic detectability may originate from low-frequency electromagnetic fields radiated by current loops generated by onboard energy systems and power-electronic equipment; motion of the platform' s metallic structure may also form motion-induced electric fields in conductive seawater, causing electromagnetic anomalies. Such features are captured by underwater electric-field sensors and shipborne electromagnetic detection arrays.

Low-frequency radiation can be approximately given by a current dipole **I**, and the far-field electric/magnetic fields decay as $1/r^2$ or $1/r^3$ (corrected according to frequency and seawater conductivity). Engineering approximation:

$$S_{em}(r) = k_{em}(f)\frac{I_{rms}}{r^{p_{em}}},$$

where $p_{em} \in [2,3]$; I_{rms} is related to propulsion-motor load and the switching frequency of power electronics.

(3) Thermal-wake and optical/infrared signature

Thermal anomalies are mainly formed by local temperature rise ΔT caused by power-cabin heat dissipation, propulsion energy consumption, and wake-turbulence mixing. This temperature difference can, within a certain range, be captured by infrared detectors, near-sea optical payloads, or satellite multi-spectral sensors.

The temperature difference from the center of the thermal wake outward along the sea surface, or at a distance r, can be approximated as an exponentially diffusive attenuation:

$$\Delta T(r) = \Delta T_0 \exp\left(-\frac{r}{L_T}\right),$$

where L_T is the thermal-diffusion decay scale related to the intensity of turbulent mixing, vessel speed, and mixing depth, and ΔT_0 is the initial temperature-difference amplitude.

Infrared and visible-light observations—especially spaceborne or airborne sensors—can identify submarine wakes through sea-surface temperature disturbances, microscale refractive-index variations, or differences in surface wave patterns. In recent years, researchers have used high-resolution infrared imaging, LiDAR, and multispectral satellite data to conduct wake identification, demonstrating that the thermal wakes of large platforms can remain observable for several tens of minutes within certain speed ranges.

(4) Gaps in existing research

Figure 2. XLAUV non-acoustic signature framework diagram

Figure 2: Figure 2. XLAUV non-acoustic signature framework diagram

In the non-acoustic domain, current research still faces several key challenges: the coupling strength among different physical models is relatively weak, and no systematic fusion framework has yet been formed for the correlation mechanisms among multiple physical fields such as magnetic, electric, thermal, and optical fields. Meanwhile, quantification of high-dimensional disturbance fields remains difficult, and the construction and application of surrogate models lack unified standards and specifications. In addition, existing models remain inadequate in their integration with real-time planning and control, making it difficult to effectively support real-time decision-making and response in dynamic environments.

Figure 2. XLAUV non-acoustic signature framework diagram

2.3 Fluid disturbances and wake signatures

The wake of an XLAUV is one of the most highly identifiable exposure sources. Wake features can be captured by multimodal sensors such as acoustic, optical, and microwave sensors (synthetic aperture radar, SAR). Even if the carrier noise is effectively suppressed, the wake may still become the dominant detection channel.

2.3.1 Vortex shedding and characteristic frequency

The platform body, hull surface, and propeller blades all generate typical vortex-shedding frequencies, characterized by a stable Strouhal-number interval, defined as $S_t = \frac{fD}{U}$, where D represents the propeller diameter or a characteristic length related to the local body, and U is the navigational speed. For large platforms, the Strouhal number is usually stable at 0.18–0.25. In addition, the resulting vortex-shedding frequency is $f_{\text{shed}} = S_t \frac{U}{D}$. This narrowband component often forms a narrowband peak in the hydrodynamic-noise spectrum, and changes in rudder angle and angle of attack can significantly alter the shedding mode.

2.3.2 Turbulent attenuation and energy-spectrum characteristics

The wake of a large platform exhibits a high initial turbulent energy E_0, with an attenuation range reaching tens to hundreds of meters, significantly affecting the imaging quality of synthetic-aperture sonar and the noise floor of passive sonar. The turbulent kinetic energy along the streamwise direction x can be represented by a power-law attenuation or exponential attenuation:

$$k(x) = k_0 \left(\frac{x}{x_0}\right)^{-n_k}, \quad n_k \approx 1.0 \sim 1.5$$

or

$$k(x) = k_0 \exp\left(-\frac{x}{L_k}\right).$$

In the inertial range, the turbulent energy spectrum approximately follows the Kolmogorov law:

$$E(k) \propto k^{-\frac{5}{3}}.$$

2.3.3 Effects of wakes on optical, acoustic, and remote-sensing detection

The wake of an XLAUV not only produces detectable features in the underwater acoustic domain, but also forms significant observable signals in optical, laser, and satellite remote sensing. The wake itself can become the main exposure source, regardless of whether the carrier is quiet. Specifically, exposure in optical/laser detection is mainly due to enhanced light scattering caused by refractive-index disturbances and microbubbles, which in turn strengthens laser-radar reflection. Exposure in acoustic detection mainly originates from low-frequency scattering caused by wake turbulence and bubbles, and the noise is easily captured by adversary passive sonar. For satellite remote-sensing exposure, the main cause is wake effects, whereby sea-surface wave-pattern disturbances are recognized by SAR/optical satellites.

Based on the above considerations, this section gives two types of physical models that can be used to quantitatively evaluate wake detectability.

(a) Wake optical detectability model aims to quantify the enhancement of optical (imaging or LiDAR) echo and the improvement in signal-to-noise ratio (signal to noise ratio, SNR) caused by the wake:

$$P_r(R) = P_t \frac{A_r}{R^2} \beta_b^{eff}(R, \lambda) \exp\left(-2\tau(R, \lambda)\right)$$

where:

$$\beta_b^{eff}(R, \lambda) = \beta_{bg}(\lambda) + \Delta\beta_{wake}(\lambda), \qquad \tau(R, \lambda) = \int_0^R \alpha_t(s, \lambda) ds$$

and the wake increment can be approximately expressed by the contributions of bubbles and turbulence as

$$\Delta\beta_{wake}(\lambda) \approx b_{bubble}(\lambda) + b_{turb}(\lambda),$$

$$b_{bubble}(\lambda) = \int_{a_{\min}}^{a_{\max}} \sigma_s(a,\lambda)n(a)da$$

Accordingly, the detectability criterion can be obtained as $SNR_{opt} = 10\log_{10}\frac{P_r}{N_{opt}}\,dB$. If $SNR_{opt} \geq SNR_{th}$ (usually $3-6\,dB$), it is judged to be detectable. Here, P_t denotes the transmitted power, A_r the receiving-aperture area, R the total "transmitter-scatterer-receiver" distance, β_b^{eff} the volume backward scattering coefficient, α_t the volume attenuation coefficient, $\sigma_s(a,\lambda)$ the scattering cross section of a single bubble, $n(a)$ the bubble-radius spectrum, N_{opt} the optical receiver noise power, and SNR_{th} the detection threshold.

(b) Wake bubble acoustic scattering and low-frequency noise model

Construct an equivalent frequency-dependent source strength $S_{wake}(f)$ by combining bubbles and turbulence; its expression is

$$S_{wake}(f) = \int_{a_{\min}}^{a_{\max}} \sigma_b(a,f)n(a)da + K\varepsilon^p f^{-q}$$

The received sound-pressure spectrum at distance r can be expressed as

$$P_r(f) \propto \frac{S_{wake}(f)}{r^2}10^{-0.1TL(f)}$$

where $TL(f)$ is the propagation loss including absorption and multipath attenuation. Therefore, the acoustic detectability criterion is

$$SNR_{ac}(f) = 10\log_{10}\frac{P_r(f)}{N_{ac}(f)}.$$

If there exists a frequency band $f \in [f_1, f_2]$ such that $SNR_{ac}(f) \geq SNR_{th}$, and the duration and bandwidth satisfy the detection-occurrence rules, then the wake can be identified by passive acoustics. In the above formulas, $\sigma_b(a,f)$ denotes the scattering and radiation cross section of a single bubble at frequency f, $n(a)$ denotes the bubble spectrum, ε denotes the turbulent energy dissipation rate, K, p, q denote empirically fitted constants, $N_{ac}(f)$ denotes the environmental and system noise spectrum, and $TL(f)$ denotes the propagation loss (dB) including scattering, absorption, and terrain/interface effects.

Figure 3: Schematic diagram of the XLAUV wake turbulent energy spectrum.

Figure 3: Schematic diagram of XLAUV wake turbulent energy spectrum.

Figure 3: Figure 3: Schematic diagram of XLAUV wake turbulent energy spectrum.

2.4 Requirements and Bottlenecks for Multi-Domain Coupling and Unified Detectability Modeling

Actual detectability is the result of coupling among multiple sources, multiple paths, and multiple sensors. To incorporate stealth constraints into planning and control, it is necessary to construct a multi-domain weighted fusion detectability function that can vary with the state and control quantities:

$$S(x,u) = w_a S_a(x,u) + w_m S_m(x,u) + w_w S_w(x,u)$$

where S_a, S_m, and S_w respectively denote detectability indicators related to acoustics, magnetic/electric/thermal fields, and wake; the weights w_a, w_m, and w_w can be dynamically adjusted according to mission phase, self-noise environment, and enemy reconnaissance means. This unified framework permits the introduction of the constraint $S(x,u) \leq S_{\max}$ in path planning, or the realization of an optimized tradeoff among stealth, energy efficiency, and speed through soft constraints/penalty functions.

Considering that the real ocean environment, equipment aging, and changes in payload will continuously affect signatures, most studies focus on physical accuracy, while non-real-time or state-dependent expressions make the models difficult to apply directly to planning and control. Different models show significant environmental differences in the variation of weights in detection probability. Therefore, although various detectability models already have mature techniques, at present there is still no general detectability function for XLAUV, nor has a cross-domain weighted detectability indicator been constructed that can be directly used for multi-objective trajectory planning and control design.

Hidden planning and multi-objective control

Source-term generation → Propagation/attenuation → Sensor response → Detection probability P_d

Noise/magnetic/wake signatures; marine environmental effects; multi-source detection; multi-domain fusion

$$S(x,u) = w_a S_a(x,u) + w_m S_m(x,u) + w_w S_w(x,u)$$

Figure 4: Schematic diagram of the multi-domain signature-generation pipeline

3. Low-Detectability Trajectory Planning

The covert-navigation requirements of XLAUV make LOTP a key component of the XLAUV mission system. Unlike traditional trajectory planning for safe obstacle avoidance or energy minimization, LOTP must generate stealth trajectories that are time-continuous, dynamically executable, and balanced across multiple objectives under the joint action of complex marine environments, dynamic adversarial search behaviors, and multi-domain detectability models. This chapter provides a systematic overview of the modeling framework of LOTP, strategies for constructing detectability surrogate models, mainstream solution methods, and their advantages and limitations in stealth applications. It also discusses coupling mechanisms at the planning, control, and material levels, with the aim of providing a foundation for subsequent control-architecture design and system optimization.

3.1 Unified Modeling Framework for the Planning Problem

Against the background of complex marine environments and adversarial detection systems, the core task of a typical LOTP problem is to minimize the overall detectability of the platform while satisfying mission constraints, such as time limits, trajectory feasibility, and power-budget constraints. A typical approach is to discretize the planning time domain as $k = 0, 1, \cdots, N$, with state x_k and control input u_k, and to integrate energy consumption, mission performance, and detectability metrics through a weighted cost function. The optimization problem can be expressed uniformly as

$$\min_{u_k} J = \sum_{k=0}^{N-1} \left(\ell_E(x_k, u_k) + \ell_T(x_k, u_k) + \lambda_S S(x_k, u_k)\right) + \phi(x_N),$$

where ℓ_E is the energy-consumption term, such as propulsion power and attitude adjustment; ℓ_T denotes mission costs such as flight time and path deviation; $S(x, u)$ is a multi-modal detectability metric including acoustic, non-acoustic, electromagnetic, optical/IR, SAR, and other modalities; and the weight λ_S regulates the trade-off between efficiency and stealth.

The state-update equation is

$$x_{k+1} = f(x_k, u_k),$$

where $f(\cdot)$ includes six-degree-of-freedom dynamics, thruster–attitude coupling relationships, and the influence of the deep-sea environment.

Constraints are usually divided into three categories:

(1) Hard constraints:

$$h(x_k, u_k) \leq 0$$

including inviolable limits such as maximum speed, depth boundaries, collision avoidance, and battery capacity.

(2) Soft constraints:

introduced into the cost in the form of slack variables ξ and penalty functions, $J \leftarrow J + \rho\|\xi\|$.

(3) Probabilistic constraints

used to handle uncertainty in enemy search strategies or randomness in sonar performance:

$$\mathbb{P}(g(x_k, u_k) \leq 0) \geq 1 - \alpha,$$

for example, requiring that the probability of being detected by passive sonar be lower than a threshold, or that the collision probability be lower than α.

3.2 Detectability Surrogate Models: Core Bottlenecks and Research Progress in LOTP

The detectability function $S(x, u)$ is the key to LOTP. However, directly using high-fidelity physical models such as acoustic propagation, electromagnetic attenuation, and vortex-wake models usually entails extremely high computational cost and cannot meet the real-time requirements of trajectory planning. Therefore, recent studies generally consider detectability surrogate models to be the most important and also the most challenging submodule in the overall planning system.

Related work has broadly formed three technical routes. The first is semi-empirical and physics-approximation modeling, commonly used for acoustic propagation loss or magnetic-anomaly prediction. By approximately expressing propagation attenuation, discrete spectral features, or field-strength distributions with a number of physical quantities, this route can provide rapid estimates with relatively strong interpretability for large-scale planning. The second is data-driven modeling, through Gaussian-process re–

regression, shallow neural networks, polynomial regression, and other methods to fit real physical models or simulation data, giving the explorability index differentiability and relatively high accuracy. In shallow-sea reverberation, complex sound-speed profiles, or nonlinear wake-disturbance fields, such methods perform particularly well. The third category is a rapidly growing hybrid modeling strategy in recent years: it uses the physical structure of acoustic or fluid models as priors, and then trains networks to fit the residuals, thereby achieving a balance between accuracy and computational cost.

Nevertheless, current explorable surrogate models still face several difficulties, such as insufficient adaptability of cross-sea-condition models, the lack of a unified expression for coupling among different modalities such as acoustic–magnetic–optical, limited interpretability of surrogate models, and the lack of real sea-trial data for calibration. Therefore, whether in offline planning or online control, explorable surrogate models are always regarded as the fundamental bottleneck of LOTP; their quality directly determines the feasibility, stability, and reliability of trajectory planning.

3.3 Mainstream LOTP Solution Paradigms and Comparison of Their Stealth Performance

Current LOTP solution strategies can generally be divided into several categories: offline global optimization, online MPC, sampling and graph-search methods, game-theoretic methods, and reinforcement learning. Since different methods perform quite differently in stealth applications, this section summarizes and compares their applicability from the perspective of XLAUV covert navigation.

3.3.1 Offline Global Optimization: Offline global optimization methods (including direct methods, NLP, sequential quadratic programming, interior-point methods, and variational methods based on optimal-control principles) have strong modeling capability and high solution quality, and are therefore very suitable for generating benchmark routes containing high-precision explorable models. For example, in long-duration covert infiltration missions in the deep sea, such methods can obtain energy-consumption–stealth Pareto fronts close to the global optimum. However, because computational costs usually grow exponentially, they are difficult to use in environments where enemy search behavior changes rapidly, and are more often used as "offline benchmark solutions" for planning systems and to provide warm starts for online algorithms.

3.3.2 Online Nonlinear Model Predictive Control: Online nonlinear model predictive control (nonlinear MPC, NMPC) is currently one of the most mature technologies in engineering applications. By continuously solving short-horizon optimal problems over a receding time domain, it enables trajectories to adapt in real time to changes in sea conditions, sound-speed profiles, and the dynamic behavior of enemy searchers. In recent years, constructing NMPC using explorable surrogate models has become mainstream in the literature; for example, Gaussian processes are used to predict acoustic exposure probability, or low-order neural networks are combined to simulate the characteristics of wake disturbances. The advantage of NMPC lies in its real-time capability and constraint-handling ability, but its performance depends heavily on the accuracy of the surrogate model; moreover, as the state dimension increases, solution speed may still become a bottleneck.

3.3.3 Sampling and Graph-Search Methods: When the terrain of the operating area is complex–such as islands and reefs, shoals, seamounts–or when the navigable region is highly nonconvex, sampling and graph-search methods have natural advantages. In stealth-planning scenarios, researchers often take acoustic exposure risk or SAR recognition risk as the edge cost of the graph, thereby constructing a "risk map" or "explorability map." Such methods can quickly provide structurally reasonable upper-level paths, but generic versions have difficulty satisfying XLAUV dynamic constraints, and the generated paths often lack smoothness. Therefore, in most engineering frameworks they are used in combination with NMPC: the former provides topologically feasible reference lines, while the latter completes dynamically executable trajectory optimization.

3.3.4 Partially Observable Markov Decision Processes and Game-Theoretic Frameworks: When the behavior of enemy searchers has strong uncertainty or when there is a clear adversarial relationship between the two sides, partially observable Markov decision processes (partially observable Markov decision process, POMDP) and game-theoretic models provide more strategic path-planning ideas. This type of method can explicitly describe the interaction among enemy-own observations, belief updates, and action strategies, and is suitable for modeling and avoiding active sonar search strategies. However, because the state space is high-dimensional and the inference process is complex, POMDP and game-theoretic methods often rely on particle approximation or policy compression; they are mostly used for strategic analysis or offline computation rather than strict real-time applications.

3.3.5 Reinforcement Learning and Its Hybrid Methods: The application of reinforcement learning (reinforcement learning, RL) in LOTP is mainly based on deep RL training of policy networks for avoiding acoustic response or multimodal detection systems. Compared with traditional model-based methods, RL is better suited to handling high-dimensional, nonlinear, or difficult-to-explicitly-model explorable functions, and its advantages are especially evident in scenarios with multiple coupled factors such as optics, SAR, or wake disturbances. However, deep RL requires enormous samples and has limited generalization ability. Engineering applications usually adopt a hybrid structure of "RL+NMPC," in which RL provides high-level strategic guidance and NMPC is responsible for executing local trajectories consistent with constraints and dynamics.

In summary, the current mainstream trend of LOTP presents a hierarchical structure combining "offline-online-intelligent" approaches: offline global optimization is responsible for generating high-quality benchmark solutions; online NMPC implements real-time stealth adjustment; sampling or graph methods provide terrain-level route guidance; and RL provides intelligent inspiration or adaptive enhancement at the strategy level [43].

3.4 Multilevel Coupling of LOTP with Control Systems and Super-Slippery Materials

With the deepening understanding of stealth performance, trajectory planning is no longer regarded as an isolated module; rather, it has significant coupling with the control layer and the materials-engineering layer. To satisfy executability requirements, the planned trajectory must match the transient response characteristics of the control system, while the spectral content of the control input directly affects source level, structural vibration, and wake-vortex characteristics. For example, abrupt changes in attitude or thrust often lead to low-frequency noise or a marked increase in the vortex-shedding mode, thereby compromising the stealth objective at the planning layer. Consequently, in recent years a research direction of "planning-control co-design" has gradually emerged, so that trajectory smoothness, spectral constraints, and the response capability of the control loop are optimized within a unified framework.

On the other hand, advances in materials engineering are also feeding back into the feasible domain of trajectory planning. For example, superhydrophobic interface technology can significantly reduce boundary-layer pressure fluctuations and friction noise, enabling the platform to maintain a lower probability of acoustic exposure even at higher speeds; changes in wake-vortex attenuation rate may also improve stealth capability under SAR and optical remote sensing. Thus, the detectability function in the planning layer essentially becomes an integrated expression of interactions among materials, dynamics, and the environment, which also means that future LOTP research will inevitably develop toward cross-scale coupling.

3.5 Engineering LOTP Framework and Evaluation System

In engineering practice, LOTP usually adopts a hierarchical structure consisting of "detectability prediction–trajectory planning–control execution–environmental feedback." The detectability predictor is responsible for using surrogate models to provide real-time exposure risks in acoustic, optical, wake, or electromagnetic domains; the planning module combines offline and online solution strategies to generate a ruler-scale trajectory; the control system performs tracking execution based on a dynamic model; and finally, closed-loop updating is realized through observations of ocean currents, sound-speed profiles, and adversary behavior. Such a structure has been gradually validated in multiple deep-sea test demonstrations, and it also facilitates modular deployment among onboard, shipborne, or shore-based systems.

When evaluating LOTP performance, researchers usually focus on the average detectability index, adversary detection probability, trajectory smoothness and control executability, computational real-time performance, and robustness under different environments. The increasingly popular Pareto-analysis method reveals systematic differences among different planning strategies by scanning the trade-off between energy consumption and stealth, providing an important reference for strategy selection in engineering applications.

4. Stealth Navigation Control System

In a confrontational environment, XLAUV stealth navigation depends not only on detectability modeling and low-detectability trajectory planning; what is more critical is the control system' s ability to regulate the executability and smoothness of the planned trajectory, as well as the spectral structure of the input. Because the control input directly affects the rate of change of platform attitude, instantaneous propulsor load, vortex-shedding modes, and structural vibration, it essentially determines how the detectability function evolves over time. Therefore, "stealth control" should be regarded as an extension of the detectability optimization problem, rather than as a traditional control task of "maintaining stability and tracking accuracy." This section will establish a unified theoretical framework for stealth control and, on this basis, review research progress in sliding-mode control, model predictive control, intelligent control, and other methods for stealth navigation, focusing on analysis of the coupling relationships among the control-input spectrum, attitude-change rate, and multi-domain detectability.

```
flowchart LR
    A[Reference trajectory and task constraints] --> B[Stealth control optimizer<br/>min J =
    B --> C[XLAUV dynamics and multi-domain detectability output]
    B <--> D[Acoustic/wake/electromagnetic<br/>detectability evaluation]
    D --> C
    C -->|Control-input spectral constraints| B
```

Figure 5. Unified optimization framework for stealth navigation control

4.1 Stealth Control Requirements and Uncertainty Modeling

Compared with traditional control systems, the optimization objective of stealth control not only requires minimizing trajectory tracking error, but also requires explicitly considering detectability risk in the control law. Therefore, the basic structure of stealth control can be summarized as the following performance index:

$$\min_{u(t)} J = \int_0^T \{\ell_{track}[x(t), u(t)] + \lambda \cdot S(x(t), u(t))\}\, dt,$$

where ℓ_{track} characterizes tracking error and control energy consumption, $S(x, u)$ is a multimodal detectability surrogate function for acoustics, magnetics, electricity, or wakes; and the weighting parameter λ determines the priority relationship between tracking accuracy and stealth performance. This structure reflects stealth control

Figure 6. Mechanistic influence pathway of the control-input spectrum on multi-domain detectability.

Figure 4: Figure 6. Mechanistic influence pathway of the control-input spectrum on multi-domain detectability.

The basic idea is that the control system must not only ensure that the trajectory is executable, but also keep the amplitude and spectrum of the control input within the "low-detectability region," so as to avoid inducing structural vibration noise peaks of high-energy sound sources or intense wake disturbances.

The above unified structure means that subsequent control methods are no longer isolated technologies, but are incorporated into the same optimization framework for discussion. For example, the switching terms of sliding-mode control directly broaden the discrete spectrum and may lead to acoustic exposure peaks; the transient response of high-gain controllers may trigger intense turbulence or changes in propulsor load; whereas NMPC and RL can keep the control input within the low-risk region of the detectability function through real-time optimization.

4.2 Mechanistic Relationship Between the Control-Input Spectrum and Multi-Domain Detectability

The essence of stealth control is the constraint on the "input spectrum," because the platform' s noise, vibration, and wake are largely determined by the spectral response of the control action. In recent years, many studies have shown that the high-frequency components of thrust and acceleration are the main triggering factors for propulsive noise, especially in the broadband region above the blade-passing frequency, where they superpose spectrally with turbulent boundary-layer noise; the rate of attitude-angle change has a direct impact on wake structure, including modulation of vortex-shedding patterns and changes in wake energy distribution; control inputs with large amplitudes or high-order derivatives excite the natural frequencies of the structure, thereby forming pronounced spectral lines in low-frequency acoustic sensitive regions.

Figure 6. Mechanistic influence pathway of the control-input spectrum on multi-domain detectability.

4.3 Intelligent Learning Methods and Hybrid Architectures

Traditional control methods mainly include PID, LQR, H_∞, and sliding-mode control. They are already quite mature in stable control of XLAUVs, but under stealth requirements, their application scope still needs to be re-examined. Linear quadratic regulators, because of their smooth control laws, are suitable for stealth-control scenarios with "low-frequency input" as the objective; H_∞ controllers can maintain output stability when environmental disturbances are

Figure 7. Hybrid implicit control architecture of NMPC and RL. Diagram labels: "RL policy learning" ; "state feedback" ; "observability evaluation" ; "NMPC real-time optimization" .

Figure 5: Figure 7. Hybrid implicit control architecture of NMPC and RL. Diagram labels: "RL policy learning"; "state feedback"; "observability evaluation" ; "NMPC real-time optimization" .

significant and exhibit strong robustness under complex shallow-sea sound fields or strong turbulence disturbances. However, sliding-mode control, owing to its inherent switching structure, produces high-frequency chattering at the control input; its spectrum lies directly in acoustically sensitive regions, making it unsuitable for stealth navigation unless softened. In recent literature, research on such methods has mainly focused on "low-frequency control" and "continuous sliding-mode substitution," reducing acoustic exposure by weakening high-frequency components [44-46].

Overall, classical control methods can provide guarantees of stability and robustness and are easy to interpret, but in multi-objective stealth control they lack a pathway for expressing detectability indicators. Therefore, more and more studies have begun to shift toward NMPC and intelligent control, explicitly incorporating detectability functions into performance indices so as to achieve more refined regulation of stealth performance.

4.4 System Integration and Engineering Implementability

Stealth model predictive control is particularly suitable for stealth-navigation tasks because it can directly optimize the two core terms in the above unified structure within a receding time domain: tracking cost and detectability cost. Existing studies have proposed NMPC-based strategies for acoustic avoidance, active acoustic-host discrimination and evasion, and wake-energy control. The core idea is to use a differentiable surrogate model to predict detectability risk in real time and incorporate it into NMPC as a constraint or cost, so that the control input automatically avoids high-risk frequency bands or power intervals.

Figure 7. Hybrid implicit control architecture of NMPC and RL

The main advantage of NMPC is that it can re-solve the optimal control law at a fixed frequency, thereby responding in real time to changes in sea conditions, sound-speed-profile drift, or enemy maneuvering strategies; moreover, it has the ability to uniformly handle attitude constraints, thrust saturation, and coupling with dynamics. Its limitation is that the solution speed is constrained by the state dimension, and surrogate-model errors may cause bias in observability evaluation. Even so, NMPC is still regarded as one of the core technical routes for implicit control, and it can form a hierarchical control architecture together with RL or graph-search methods.

4.5 System Integration and Engineering Realizability

With the development of deep-learning technology, RL, imitation learning (IL), and adaptive control methods based on policy gradients have rapidly become widespread in the field of AUV control. In recent years, RL-related research on UUV implicit control, acoustic avoidance, and multi-agent confrontation has attracted attention. Representative work includes using deep Q-networks and policy-gradient methods to realize maneuvering avoidance against active sonar, modeling the search–avoidance confrontation process through multi-agent RL, and using Actor-Critic structures to learn explorable-space mappings.

Intelligent control methods can learn high-dimensional and nonlinear observability structures without explicit physical models, and are especially suitable for scenarios in which multi-domain observability coupling is complex or surrogate models are difficult to construct. However, their shortcomings lie in the enormous sample demand, dependence of generalization on the training distribution, and difficulty in providing interpretability. Therefore, in engineering applications they are usually combined with NMPC to build hybrid systems: RL provides high-level policies or serves as a warm start for NMPC, while NMPC guarantees local executability and stability. The software architecture of this type of combination is gradually maturing in practical AUV systems.

Based on the above unified structure of implicit-control performance indicators, the mechanisms and applicability of mainstream control methods in stealth-navigation applications have been reviewed. The coupling relationships among control-input spectra, attitude changes, and multi-modal observability constitute the physical basis of implicit control, while the observability surrogate model and real-time optimization capability determine the engineering feasibility and performance upper bound of the control system. The current research trend is gradually shifting from traditional control toward NMPC dominance with RL assistance, coordinated planning–control design, and cross-domain coupling among materials, dynamics, and control. Future implicit-control systems should further realize multi-modal coupling among acoustics, turbulence, electromagnetics, optics, and other modalities.

5. Superlubrication Technology: Mechanisms, Numerical Modeling, and Engineering Applications

In large underwater platforms, mechanical friction radiates acoustic energy to the outside world through a clear energy-cascade pathway: fluctuations in frictional force at the contact interface first generate microscopic excitation, which is then amplified through the shaft system and the structural path of the hull and coupled into the water body, ultimately forming a radiated sound field that can be captured by passive or active sonar.

5.1 Mechanism of Mechanical Friction in the Noise Link of Underwater Platforms

For XLAUVs, because of their high payload, long shaft system, and complex transmission chain, the broadband noise and discrete components caused by friction usually account for an important proportion in the range from tens of hertz to kilohertz, and are especially prominent under low-speed, long-endurance operating conditions. Therefore, from the perspectives of reducing energy consumption and enhancing stealth, reducing the friction coefficient μ, suppressing friction-force fluctuations ΔF_f, and improving the stability of lubricant-film thickness h are not only engineering means for improving propulsion efficiency, but also direct technical pathways for suppressing structural–acoustic transmission links and reducing observability.

5.2 Physical Principles and Mainstream Implementation Routes of Superlubrication Technology

Superlubrication technology aims to reduce the interfacial friction coefficient to a magnitude that can be called a "superlubrication regime" in engineering terms (typically $\mu < 10^{-2}$, and even reaching $\mu \approx 10^{-3} \sim 10^{-4}$). In marine-equipment applications, currently feasible technical routes include surface functionalization represented by solid coatings, lubricating-liquid engineering represented by nanoparticles or functional additives, interfacial chemical lubrication schemes represented by ionic liquids, and surface-engineering methods such as hydrodynamic support and lubricant-reservoir effects realized through surface microstructuring. Diamond-like carbon coatings are widely used on bearing raceways and meshing tooth surfaces because of their high hardness and low-friction characteristics; graphite and layered sulfides (such as MoS_2 and WS_2), relying on interlayer sliding mechanisms, exhibit good shear performance under saline conditions; nanoparticles (for example

MoS_2, TiO_2, and BN) are commonly used to form repairable friction interfaces, reduce wear, and produce a "rolling-bead effect" during sliding; ionic liquids, meanwhile, exploit the adsorbed film they form on metal surfaces to provide lubricating stability under high viscosity indices. Surface microstructuring techniques such as laser surface texturing (LST) construct arrays of micro-dimples that can serve both as reservoirs for lubricants and as local hydrodynamic supports, thereby improving the uniformity and stability of lubricating-film thickness. The special requirements of marine conditions—high-salinity corrosion, deep-sea high pressure (>30 Mpa), temperature gradients, sea-sand abrasion, and biofouling—impose stringent constraints on material selection, coating adhesion, film-failure mechanisms, and durability for the above technologies. Therefore, engineering applications must take into account long-term stability and assessments of marine durability.

5.3 Numerical and Experimental Evaluation Methods

Performance evaluation of superlubrication schemes is often built upon a coupled "friction–vibration–acoustic" analysis framework. The friction force can be modeled using mixed lubrication and Stribeck-type expressions, commonly written as $F_f = \mu(v,h,p)N$, with the friction coefficient decomposed into the superposed form of boundary friction μ_b, fluid-film friction $\mu_{hd}(v,h,p)$, and adsorption-film contribution μ_{as}: $\mu = \mu_b + \mu_{hd}(v,h,p) + \mu_{as}$, where each term depends on sliding velocity v, film thickness h, and contact pressure p. The friction excitation acts as a time-dependent external input into the structural-dynamics equation, usually described in matrix form as $M\ddot{x}+C\dot{x}+Kx = BF_f(t)$, and the structural response is then solved by finite-element or modal-superposition methods. Finally, the coupling between the structural surface normal velocity $v_n(\omega)$ and the acoustic propagation operator $G(\omega)$ is used to estimate the frequency-domain sound-pressure distribution, with a typical expression $p(\omega) = \int_s G(\omega)v_n(\omega)dS$. This coupling chain enables changes in interfacial friction to be quantified as changes in sound-pressure spectra, thereby providing a physically traceable measurement method for stealth evaluation.

Experimental validation remains the core link in the engineering of superlubrication technologies, and should cover the full life cycle from material screening to system-level sea trials. A common hierarchical testing process includes small-scale experiments (ball-on-disk, four-ball devices, etc.) to evaluate the friction-coefficient increment $\Delta\mu$ and wear rate; water-tank and towing tests to measure, under controlled seawater conditions, the suppression effect of coatings or lubricants on the noise spectra of propeller shafts and gears; and final prototype sea trials to measure the in-service noise changes of propulsion shafts, gears, and sealing systems under different depth and speed conditions, and to evaluate durability under real sea states. Engineering metrics for comparison include the friction-reduction rate $\Delta\mu = \frac{(\mu_0-\mu_1)}{\mu_0}$, the noise-spectrum reduction ΔL_p (with the frequency band of concern usually being broadband changes in 10–1000 Hz), the power-saving ratio $\eta = \frac{\Delta P_{in}}{P_{in}}$, as well as long-cycle lifetime, film-failure time, and corrosion-degradation rate. These indicators not only measure the performance improvement of individual components, but also constitute input parameters for evaluating system-level stealth capability.

5.4 Coupled Effects on Trajectory, Control, and Observability Models

Superlubrication technology has multilayered system-level consequences for the performance of XLAUV systems. When the friction force is reduced from $F_f = \mu_0 N$ to $F'_f = \mu' N$ (and $\mu' \ll \mu_0$), the propulsion equation can change from $T - D(v) - F_f = m\dot{v}$ to $T - D(v) - F'_f = m\dot{v}$. Under steady cruising conditions, this reduction in friction is directly converted into improved propulsive efficiency, so that the thrust T required to maintain a constant mission speed decreases, or a higher cruising speed can be achieved at the same power consumption. More importantly, reduced friction is usually accompanied by a decrease in the rate of change of control inputs, which weakens high-frequency excitation of the propulsion structure and flow field, manifested as a decrease in the intensity of structural radiated sound. If the structure-related observability term is expressed as $S_{struct} \propto k_s F_f^2$, then when F_f is reduced to F_F', the source strength decreases quadratically, providing a quantifiable stealth gain for the planning layer. In the optimal problem of trajectory planning, this effect can be realized by parameterizing material properties as coefficients within the observability cost function, thereby achieving speed-profile and path optimization based on material selection; that is, in the cost function $J = \sum \ell_E + \lambda_{sS}(x, u; \mu')$, the optimal trajectory is recomputed using the new value of μ', yielding a better energy-consumption–stealth trade-off.

At the control level, friction reduction makes the dynamics model closer to a linearized description, and the resistance varies more smoothly with speed, thereby facilitating the performance of MPC and robust controllers. Specifically, smaller and smoother friction terms reduce the magnitude of model error, simplify the complexity of the surrogate model required for online optimization, improve prediction reliability, and reduce the risk of introducing high-frequency chattering into the control law. Therefore, the engineering of superlubricating materials not only reduces observability at the source, but also has a positive impact on the realizability and performance limits of planning–control coupling.

For ease of engineering implementation, it is recommended that the influence of superlubricating materials be embodied in system design through a modular process: first, coating/lubrication model parameters (such as μ', film-failure time t_{fail}, corrosion rate, etc.) are used as inputs to update the propulsion-dynamics model and calculate a new observability surrogate $S(x, u; \mu')$; next, the optimal trajectory and control strategy are re-solved in the planner (offline baseline and online NMPC); finally, the actual improvement magnitudes of $P_d(t)$ and $S(t)$ are evaluated through multilayer validation chains such as HIL/SIL, tank tests, and sea trials. This closed-loop process realizes an integrated engineering validation route of "materials–dynamics–stealth performance–strategy (planning/control)," enabling superlubrication technology to transition from single-material improvement to system-level stealth-capability enhancement.

In summary, superlubrication technology has significant engineering potential in reducing friction, suppressing fluctuations in friction-force spectra, and improving propulsive efficiency. Its true stealth value comes from the ability to be quantified and integrated into observability surrogate models and trajectory-control joint optimization processes. Future research needs to focus on solving the durability and film-failure mechanisms of materials during long-term deep-sea service, and on complex marine

under current-generation proxy models, as well as quantification methods that translate the local friction-suppression effect in system-level tests into observable stealth benefits at the platform end.

6. Development Trends, Engineering Pathways, and Research Priorities

Stealth-navigation technology is undergoing a paradigm shift from "single-domain noise reduction"toward "multi-domain observability management."Traditional stealth research usually regards acoustic noise reduction as the core objective, whereas the new generation of counter-submersible systems integrates multiple physical domains—including acoustics, optics, infrared, magnetic anomalies, electromagnetics, SAR, and fluid disturbances—so that suppression of a single noise source can no longer satisfy the stealth requirements under complex confrontation conditions. At the same time, extra-large platforms such as XLAUVs are characterized by high inertia, long axial extent, large-scale heat dissipation, and strongly coupled flow-solid fields, which make their multi-domain signatures highly correlated and nonlinearly propagated. It is therefore urgent to adopt interdisciplinary systems methods for stealth design. Based on this trend, this chapter provides a comprehensive discussion and analysis centered on technical priorities, engineering pathways, and key scientific and engineering issues, and proposes future research directions.

6.1 From "Single-Source Noise Reduction" to "Closed-Loop Observability"

The construction of multi-domain observability models and the development of embedded proxy models are the highest priorities in the current research system. A survey of the relevant literature shows that, in recent years, high-precision models have appeared in areas such as acoustic propagation, optical scattering, wake simulation, and magnetic-anomaly prediction. However, these models mostly focus on single physical domains and are difficult to embed directly into planning and control modules. Therefore, constructing multi-domain observability proxies that can operate at the control frequency—including physics-prior-based low-dimensional mappings, Gaussian processes, lightweight neural networks, and adaptive proxies—is the key foundation of the planning-control closed loop.

Table 6-1. Summary of Low-Observability

Technical direction	Technical maturity (TRL)	Impact on overall observability	Embeddability in planning/control	Engineering implementation cycle	Overall priority
Multi-domain observability modeling (sound/light/magnetic/wake/electric field)	Medium	Extremely high (source-level)	Strong (determines the reliability of the cost function $S(x, u)$)	Medium	Highest
Observability proxy model (GP/NN/physics-prior low-dimensional mapping)	Medium	High	Extremely strong (determines the real-time performance of NMPC/DRL)	Medium	Extremely high
Trajectory-control coupling (NMPC/stick control, DRL)	Medium-high	High	Extremely strong (forms a “closed loop of observability”)	Medium	High
Materials and structural engineering (superhydrophobic coatings, vibration reduction, sealing, low-noise tooth surfaces)	High (local components)	Medium-high	Medium (affects dynamics and source terms)	Long	Medium-high

Technical direction	Technical maturity (TRL)	Impact on overall observability	Embeddability in planning/control	Engineering implementation cycle	Overall priority
Multi-platform collaborative stealth (mother ship-sub-vehicle/cluster/formation mode)	Low-medium	High (system-level)	Weak-medium (depends on communications and strategy layer)	Long	Medium
Wake control and fluid stealth (boundary-layer control)	Low-medium	Medium	Weak	Long	Relatively low (medium-long term)

On this basis, the trajectory-control coupling framework becomes the core technical direction in stealth navigation. Current mainstream research methods (NMPC, DRL, game theory, hierarchical strategic control, etc.) all take observability as a cost function or constraint term and introduce structured stealth-control objectives. However, literature reviews indicate that the overwhelming majority of studies still adopt the form of "fixed environmental model + offline planning," lacking an online updating mechanism for observability as operating conditions change. Therefore, unifying observability models, policy learning, and execution control into a closed-loop system is a shared need in current scientific research and engineering.

Materials and structural engineering—such as superhydrophobic coatings, low-noise meshing tooth surfaces, damping layers, and wake-control interfaces—constitutes the physical foundation of stealth navigation. Its engineering maturity is relatively high, but because of factors such as deep-sea durability, corrosion, and reliability certification, the engineering implementation cycle is usually significantly longer than that of models and control methods. Therefore, in priority ranking, the importance of materials engineering lies not in independent noise-reduction capability, but in whether it can form system-level coordination with the planning-control layer.

6.2 Engineering Roadmap

To achieve "controllable, verifiable, and deployable"stealth-navigation capability, the best approach is to adopt a staged engineering pathway from small to large, gradually expanding from component-level verification to system-level sea trials and prototype deployment.

Table 6-2. Challenges at the Scientific-Research and Engineering Levels

Research Challenges	Engineering Realities
Multi-domain observability models have rich physical mechanisms, but most are single-domain	Engineering requires millisecond-level computable embedded models, with full
High-precision simulation is difficult to apply in real time	Computational-volume contradiction between full-scale CFD/acoustic propagation
DRL/NMPC can implement implicit optimization in simulation	In real sea conditions, a large amount of calibration data is lacking, and model mismatch makes the strategy undeployable
Superlubric coatings and low-noise friction interfaces show excellent performance in the laboratory	Deep-sea high pressure, strategy, and abrasion lead to unknown material degradation curves, and long-term reliability data are lacking
Multi-domain surrogate models can be constructed through machine learning	Sea-trial data are extremely scarce and subject to confidentiality restrictions, making it difficult to train general-purpose surrogates
Explorability constraints can be explicitly modeled in theory	Most engineering control still centers on "robustness" and has not incorporated online explorability constraints
Multi-platform collaborative stealth models are theoretically feasible	Engineering communication links, synchronization mechanisms, data fusion, and standardization are all not yet mature

First stage: Focus on physical validation of materials and key components; carry out tribological and acoustic tests on key noise sources such as bearings and gears (including coating friction-coefficient curves, friction–vibration–acoustic coupling responses, and seawater corrosion durability assessment), so as to obtain high-quality data needed for constructing surrogate models and calibrating numerical models.

Second stage: Integrate subsystems such as superlubrication technology and vibration-damping supports into test platforms for propeller shafts and power cabins; in combination with tank and towing tests, conduct structural–acoustic–fluid multi-domain response measurements; and, on this basis, train signature surrogate models and offline optimizers, forming a reproducible simulation–test closed loop.

Third stage: Enter controlled sea trials and conduct system-level verification in restricted sea areas: use underwater acoustic arrays, optical imaging, wake measurements, and other means to verify the actual management capability of online planners (NMPC/rudder-stick control) for explorability constraints, and evaluate indicators such as P_d and S under real disturbances.

Fourth stage: Carry out long-period cruising and mission verification on prototype platforms, examining the collaborative performance of the strategy layer (DRL/POMDP) and the execution layer (MPC/tracking control), while also completing reliability, durability, and full-life-cycle assessments. This evolutionary route can not only gradually accumulate data for model training and validation, but also control risks and optimize resource input at each hierarchical level, thereby reducing the probability of overall engineering failure.

6.3 Open Problems

Although the above path is operable, several fundamental problems still need to be solved before concealed navigation technology can obtain broad engineering application.

First is the problem of constructing an integrated **multi-domain simulation system**. At present, models for acoustics, optics, fluid wakes, electromagnetics, and other domains are mostly built independently by tools from different disciplines and at different scales; effective coupling schemes are lacking, making it difficult for the strategy layer to carry out cross-domain trade-offs and causing scale mismatch (for example, the frequency-domain span ranges from Hz to kHz, and the spatial scale ranges from cm to tens of meters). In the future, cross-domain coupling frameworks and numerical solution strategies need to be developed that both preserve the physical constraints of each domain and output, at controllable computational cost, signature estimates usable for planning/control.

Second is the problem of **online signature updating**. Real sea conditions and equipment states change over time, and static surrogates are difficult to make satisfy task-period reliability requirements. Therefore, online learning/calibration methods with uncertainty quantification capability need to be studied, so as to ensure that $S(x, u)$ is corrected in real time during the mission process and that credible intervals are provided.

Third, **the scarcity of test data** is one of the bottlenecks for practical engineering implementation; confidentiality and the high cost of expensive sea trials make public data extremely limited. For this reason, the research community should explore shared-test agreements, formulate mechanisms for data desensitization and hierarchical release, and develop small-sample learning methods based on physical priors in order to reduce dependence on large amounts of labeled data.

Fourth, **the long-term reliability of materials** is still unclear. For example, the corrosion, wear, and performance-degradation laws of superlubric coatings and ionic liquids under long-period deep-sea conditions require systematic quantitative research; the relevant results will directly affect cost–benefit analysis for material replacement.

Fifth, issues of **regulations and standards** related to industrialization also cannot be ignored. At present, underwater-equipment noise and wake control lack unified international standards, and material replacement and structural modification involve safety/certification and high-cost investment. It is urgent to carry out interdisciplinary standardization research and economic evaluation.

6.4 Conclusions and Recommendations

In summary, the next stage of research and engineering work should take collaborative advancement of "model–surrogate–control–materials" as the basic strategy. In the short term, priority should be given to building multi-domain, embeddable explorability models and high-confidence signature surrogates to support reliable deployment of online strategies such as NMPC and DRL; in the medium term, subsystem integration and controlled sea trials should be used to verify planning–control–materials coupling effects and to form reproducible validation procedures; in the long term, the focus should be placed on multi-platform collaboration, standard setting, and full-life-cycle engineering issues. Specific recommendations include: promoting the sharing and standardization of interdisciplinary test data, developing online surrogate models with uncertainty characterization, implementing joint optimization of $S(x, u)$ within NMPC and DRL frameworks, and carrying out super-

material durability in deep-sea environments. Through the above orderly advancement, it is expected that stealth navigation can gradually progress from a research paradigm to a verifiable, reliable, and deployable engineering capability, laying the foundation for the design and operational application of next-generation low-detectability underwater platforms.

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