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Disturbance-Rejection Control Strategies and Algorithms for Autonomous Underwater Vehicles and Unmanned Aerial Vehicles: A Cross-Domain Survey

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Abstract. When autonomous underwater vehicles (AUVs) and unmanned aerial vehicles (UAVs) operate in environments with complex fluid disturbances, their disturbance-rejection capability is critical to attitude stability and mission reliability. From a cross-domain perspective, this paper reviews representative disturbance-rejection control strategies and algorithms for these two platforms. First, it compares AUVs and UAVs in terms of dynamic structure, medium properties, and the frequency content and predictability of disturbances, and highlight the distinct requirements imposed by low-frequency, slowly varying disturbances and high-frequency stochastic disturbances on control bandwidth and compensation mechanisms. The paper then focuses on sliding mode control (SMC), model predictive control (MPC), active disturbance rejection control (ADRC), and intelligent approaches based on deep reinforcement learning and neural networks. It summarizes their representative applications, robustness properties, and applicability under different disturbance types and constraint conditions. On this basis, comparative analyses and selection guidelines for disturbance-rejection control of AUVs and UAVs are provided to support the design of control strategies in practical engineering scenarios.

Keywords: autonomous underwater vehicle (AUV), unmanned aerial vehicle (UAV), disturbancerejection control, fluid disturbances

1. Introduction

In recent years, autonomous underwater vehicles (AUVs) and unmanned aerial vehicles (UAVs) have undertaken a wide range of missions in hazardous and unstructured environments. In such dynamic and uncertain settings, fluid disturbances frequently emerge as a critical factor constraining system performance and mission success [1]. With the advancement of related research, disturbancerejection control has gradually evolved from traditional linear feedback to "active disturbance rejection" and "intelligent robust control". Meanwhile, the limitations of PID and analogous methods under intense, uncertain disturbances have grown increasingly apparent [2,3]. For UAVs in particular, advanced nonlinear control strategies that integrate multiple sensors and hybrid control schemes have been systematically summarized in [4]. Motivated by recent research trends, active disturbance rejection control (ADRC), sliding mode control (SMC), model predictive control (MPC), and deep reinforcement learning (DRL) have become major focuses in disturbance-rejection studies. However, existing papers are usually restricted to a single domain. Surveys on AUV control mostly center on traditional methods such as PID and SMC, with limited systematic discussion of intelligent disturbancerejection strategies [3]. Surveys on UAV control are largely confined to the aerospace field, lacking cross-domain comparisons of disturbance mechanisms with underwater systems [2]. Additionally, although meta-heuristic algorithms related to high-level planning have been extensively studied, discussion of low-level disturbance-rejection mechanisms remains relatively insufficient [5].

Against this background, this paper compares the commonalities and differences between the two platforms in terms of dynamic structure, disturbance frequency distribution, and predictability. Unlike existing surveys, this paper not only summarizes the technical features of mainstream methods, but also further analyzes their applicability across diverse disturbance environments. On this basis, a comparative framework for disturbance-rejection control of AUVs and UAVs is established, aimed at addressing the gap in cross-domain research.

2. Dynamic mechanisms and environmental disturbances

2.1. Differences in system dynamics: effects of medium density and coupling structure

The dynamic differences between AUVs and UAVs are primarily dictated by the density of the operating medium and the resulting damping effects. AUVs operate in a high-density aquatic environment with significant added mass, which results in a nondiagonal inertia matrix and strong coupling between degrees of freedom. Moreover, hydrodynamic drag exhibits strong nonlinearity, and the influence of ocean currents further amplifies parametric uncertainty [6]. Consequently, the dynamic complexity of AUVs mainly stems from strong coupling and parameter uncertainty in a dense medium.

By contrast, UAVs operate in low-density air, where added mass can be neglected and aerodynamic damping is minimal. The system lacks passive stability and relies entirely on a high-bandwidth attitude feedback loop to maintain stability. Meanwhile, various aerodynamic disturbances are highly time-varying, rendering the fast dynamics more vulnerable to perturbations [7]. In summary, AUVs confront core challenges from strong coupling and parameter uncertainty in dense media, while UAVs contend with fast dynamics and highly time-varying aerodynamic disturbances under low damping.

2.2. Differences in environmental disturbances: frequency structure and predictability

Disturbances acting on AUVs and UAVs differ significantly in frequency distribution, time variability, and predictability. Underwater disturbances typically fall within the low- to medium-frequency range and exhibit slow temporal variation [8]. Ocean currents and waves exhibit relatively stable spectral structures and spatial correlations,inducing significant cumulative drift effects that exert long-term impacts on the trajectory accuracy of AUVs [9].

By contrast, gusts, wakes, and ground effects encountered by UAVs are characterized by high-frequency content, rapid variation, and strong randomness. Under low-damping conditions, these disturbances are rapidly propagated to the attitude and position control channels, directly impairing flight stability [7]. Overall, underwater disturbances tend to be slower and more predictable, while aerial disturbances are faster and more stochastic.

2.3. Control requirements under the interaction between system dynamics and disturbances

These characteristics collectively define the disturbance-rejection control requirements of the two platforms. For AUVs, ocean currents and waves are primarily low- to medium-frequency, slowly varying disturbances with significant cumulative drift effects. They exert long-term impacts on trajectory maintenance and energy consumption, so the control system needs to emphasize steady-state accuracy and compensation capabilities against slowly varying disturbances.

For UAVs, high-frequency random disturbances such as gusts and wakes easily trigger attitude oscillations under low-damping structures. This demands high-bandwidth attitude control loops and fast actuator responses to suppress transient perturbations. For both platforms, key performance metrics include steady-state accuracy, transient response, and robustness to modeling errors, which are used in the subsequent comparison of control strategies.

3. Survey of disturbance-rejection control algorithms

3.1. Sliding Mode Control (SMC)

Sliding mode control (SMC) is widely used for disturbance rejection in AUVs and UAVs because of its robustness to matched disturbances and modeling uncertainty [10-15]. By employing switching control to drive the system state to a sliding surface and maintain it there, SMC maintains trajectory tracking under parameter perturbations and external disturbances. However, high-frequency switching induces chattering and accelerates actuator degradation. Additionally, linear sliding surfaces only guarantee asymptotic convergence, with limited response under strong disturbances or aggressive maneuvering scenarios.

To improve convergence speed and suppress chattering, variants such as nonsingular terminal, second-order, and integral, incorporate nonlinear or higher-order sliding surfaces to enable finite-time convergence [10]. In AUV applications, hydrodynamic forces and ocean currents that are difficult to model are often treated as lumped disturbances, and integral SMC is used to compensate these uncertainties [12]. For actuator saturation and coupling structures, adaptive SMC uses auxiliary systems to compensate saturation errors. Hierarchical SMC exploits a multi-layer framework to address multi-input coupling. Overall, SMC features a simple and strong robustness, but parameter tuning remains highly experience-dependent. A trade-off is required between chattering suppression and actuator lifespan.

3.2. Model Predictive Control (MPC) and nonlinear extensions

Model predictive control (MPC) and its nonlinear variants (NMPC) employ receding-horizon optimization to explicitly address multivariable coupling and state/input constraints. They have become key solutions for high-precision trajectory and attitude control of AUVs and UAVs [14,15]. For underactuated AUVs, NMPC utilizes nonlinear hydrodynamic and buoyancy models to prevent linearization failures during large-attitude maneuvers, while accounting for thruster saturation and attitude constraints

Unmodeled dynamics and external disturbances, such as ocean currents and gusts, degrade the robustness of MPC. Tube-based robust MPC adopts an auxiliary control law to contract the perturbed trajectory within a “tube” around the nominal trajectory. It employs input-to-state stability conditions to guarantee closed-loop stability [16]. To enhance disturbance estimation, many studies integrate fast terminal extended state observers derived from ADRC, which treat lumped disturbance

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as an additional state to be estimated and compensated uniformly, thereby reducing velocity fluctuations and improving tracking accuracy.

MPC exhibits clear advantages in multi-objective optimization. For energy efficiency, NMPC exploits favorable ocean currents to reduce thruster forces and improve energy efficiency. For path planning, NMPC with obstacle-avoidance and speed constraints can generate feasible trajectories in dynamically cluttered environments. However, MPC is sensitive to model accuracy and computational resources. Its performance tends to degrade under strong disturbances or limited onboard computation.

3.3. Active Disturbance Rejection Control (ADRC)

Active disturbance rejection control (ADRC) employs an extended state observer (ESO) to lump unmodeled dynamics and external disturbances into a “total disturbance,” which is estimated and compensated in real time, enabling suppression of multi-source disturbances via a relatively simple control architecture [17]. Compared with traditional PID control, ADRC has lower reliance on precise plant models and only requires knowledge of the system’s relative order to construct a state-error feedback control law. It has thus become a key candidate to replace PID in AUV and UAV applications [18-22].

For the fast dynamics of UAVs, research seeks a balance between transient performance and structural complexity: nonlinear ADRCdelivers superior short-term response, whereas linear ADRC is easier to tune, making it more widely adopted in engineering practice. Some studies develop hybrid control frameworks integrating ADRC and SMC, where the ESO smooths the chattering introduced by the sliding mode while maintaining robust feedback characteristics [18]. For AUVs, where input delays and significant inertia uncertainty are prevalent, the bandwidth of conventional ESOs is limited. Intermediate observer (IO) schemes employ auxiliary variables to estimate states and disturbances simultaneously and act as predictors to compensate time-varying input delays; fractional-order ADRC leverages the long-memory property of fractional calculus to better model and suppress fluid damping with long-tail characteristics [17]. In summary, ADRC can improve disturbance attenuation without significantly increasing structural complexity. However, ESO bandwidth selection, parameter tuning, and consistency analysis under input constraints remain major challenges in engineering applications.

3.4. Intelligent algorithms based on deep reinforcement learning and neural networks

Intelligent control strategies, especially deep reinforcement learning (DRL) and neural networks (NNs), have become key tools for AUVs and UAVs operating in highly nonlinear and uncertain environments. They can formulate disturbance-rejection control laws with low reliance on precise models or even without explicit analytical models. Data-driven NN-based methods can compensate for unmodeled dynamics. For example, introducing a Sigma–Pi neural network (SPNN) into dynamic inversion uses simple adaptive laws to reduce inversion errors and enhance tracking performance [20]. For underwater applications, deep reinforcement learning has also been applied to dynamic target tracking of AUVs [21].

Under strong disturbance conditions, intelligent algorithms promote a shift in control design from “observation” to “approximation”. Embedding adaptive radial basis function neural networks (RBFNNs) into ADRC enables more accurate estimation of the total disturbance and improves robustness [19]. Geometric control on SE(3) combined with deep NNs can counteract nonlinear disturbances during large maneuvers while ensuring ultimately bounded stability [22]. Additionally,

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DRL based on echo state networks (ESNs) can exploit reservoir computing to extract temporal features, allowing agents to obtain control policies without explicit analytical models in some studies [23].

Given the limitations of pure learning-based methods, such as high computational costs and lack of stability guarantees, current research tends to develop hybrid frameworks of "deterministic control plus intelligent compensation". In such frameworks, Lyapunov-based methods provide stability guarantees, while adaptive NN weights compensate for residual uncertainties. This enables safer and more generalizable disturbance-rejection control in complex environments [20,22]. It should be noted that most of these algorithms still depend on specific models and experimental conditions, and their engineering applicability requires further validation.

4. Applicability of disturbancerejection methods to AUVs and UAVs

As discussed in Section 2, the distinct disturbance frequency profiles of AUVs (low-frequency) and UAVs (high-frequency) dictate specific control requirements. Sliding mode control (SMC), owing to its robustness against matched disturbances, has been widely applied to both platforms [10-15]. For AUVs, where slowly varying currents and model uncertainties are prominent, SMC can improve trajectory maintenance and attitude stability [10,12]. For UAVs, high-frequency gusts tend to amplify chattering caused by switching control. Thus, terminal or second-order sliding modes are often adopted in practice to balance disturbance-rejection capability and actuator loading [11,13]. Model predictive control (MPC) can explicitly address multivariable coupling and physical constraints, offering advantages for AUV trajectory keeping and complex hydrodynamic path planning [14-18]. For UAVs, MPC's receding-horizon structure is well-suited for high-bandwidth attitude control.. However, its performance is sensitive to model accuracy and computational resources, degrading under strong aerodynamic disturbances or limited onboard computation [15]. Active disturbance rejection control (ADRC) achieves unified estimation of lumped disturbance through an extended state observer and exhibits strong transferability and model independence for both slowly varying underwater disturbances and multi-source random disturbances in the aerospace domain [17-22]. For both platforms, it serves as a low-model-dependence alternative that enhances steady-state accuracy and disturbance-rejection performance.

Intelligent methods such as neural networks and deep reinforcement learning can approximate unmodeled dynamics and act as compensation modules to enhance adaptability in complex environments. Preliminary engineering validations have been reported for both AUVs and UAVs [23-25]. In AUV applications, greater emphasis is placed on disturbance prediction and model-based compensation to suppress long-term drift. In UAV applications, higher priority is given to high-bandwidth sensing, fast actuator response, and suppression of transient disturbances [22].

5. Conclusion

This paper has surveyed disturbance-rejection control for AUVs and UAVs, highlighting disturbance mechanisms and control strategies. The paper first compares the two platforms in terms of inertia structure, medium damping, and disturbance frequency distribution. It then analyzes how low-frequency ocean currents and high-frequency gusts affect control bandwidth and compensation mechanisms. The paper summarizes representative applications, robustness properties, and applicability trends of SMC, MPC, ADRC, and intelligent methods such as neural networks and deep reinforcement learning on both platforms. Despite ongoing advancements in these methods, crossenvironment consistency, verifiability, and engineering deployability remain major bottlenecks.

Future research can further advance high-fidelity disturbance modeling, simplify control structures, and develop verifiable model–data fusion schemes. These efforts will enhance the long-term autonomy and mission reliability of unmanned systems operating under complex disturbances [24].

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