ISSN: 2710-0588

Application of AUV Cluster Control in Deep-Sea Pipeline Inspection

Rongjie Cai[1,+,*], Rui Gao[1,+], Yingzhi Ma[2,+], Yuexuan Liu[3], Xubin Zhao[1], Yangyang Zhang[1], Xin Guo[2], Zhiwen Yu[1], Kelan Huang[1]

[1] Guangdong Ocean University, St. Petersburg Institute of Shipbuilding and Marine Technology, Zhanjiang 524088, Guangdong, China

[2] Guangdong Ocean University, College of electronics and information engineering, Zhanjiang 524088, Guangdong, China

[3] Guangdong Ocean University, College of Literature and News Communication, Zhanjiang 524088, Guangdong, China

[*]Corresponding author: Rongjie Cai

[+]Co-first author

Abstract

With the rapid development of offshore oil and gas resources exploitation, deep-sea pipelines, as the core of marine energy transportation, face severe challenges in regular inspection and maintenance. Autonomous Underwater Vehicle (AUV) cluster technology has become a promising solution to address the limitations of single AUV in efficiency, coverage, and reliability during deep-sea operations. This paper focuses on the application of AUV cluster control in deep-sea pipeline inspection. First, it analyzes the technical difficulties of deep-sea pipeline inspection and the advantages of AUV cluster systems. Then, it proposes a leader-follower formation control strategy based on backstepping neural network to solve the problems of underactuation, nonlinear dynamics, and communication constraints of AUVs in marine environments. The kinematic and dynamic models of AUV clusters are established, and the stability of the control system is verified through theoretical derivation. Finally, simulation experiments and sea trial data are presented to demonstrate the effectiveness of the proposed control strategy in improving inspection efficiency and data accuracy. The results show that the AUV cluster system can complete pipeline inspection tasks with an average error of less than 5% under complex deep-sea conditions, which significantly outperforms the single AUV operation mode. This research provides a reliable technical support for the intelligent and efficient inspection of deep-sea pipelines.

Keywords

AUV Cluster, Formation Control, Deep-sea Pipeline, Inspection Technology, Backstepping Neural Network.

1. Introduction

Deep-sea pipelines play an irreplaceable role in the transportation of offshore oil, gas, and other energy resources, and their safe operation is crucial to the stability of marine energy supply chains. However, the deep-sea environment is characterized by high pressure, low temperature, strong currents, and limited visibility, which makes pipeline inspection extremely difficult. Traditional inspection methods, such as manned submersibles and single AUVs, have inherent limitations: manned submersibles are high-cost and risky, while single AUVs are limited by

ISSN: 2710-0588

battery capacity, payload, and operational efficiency, making it difficult to meet the needs of large-scale and high-frequency pipeline inspections [1].

In recent years, AUV cluster technology has developed rapidly, which realizes collaborative operations through multiple AUVs, effectively overcoming the shortcomings of single AUV systems. Compared with traditional inspection methods, AUV clusters have significant advantages in terms of task coverage, operation efficiency, and fault tolerance. For example, multiple AUVs can perform parallel inspections along different segments of the pipeline, greatly reducing the total inspection time; when individual AUVs fail, the remaining AUVs can reconfigure their formation to ensure the continuity of the inspection task [2]. However, the application of AUV cluster control in deep-sea pipeline inspection still faces many technical challenges, including nonlinear dynamics of AUVs, time-varying marine environmental disturbances, limited underwater communication bandwidth, and precise formation maintenance [3].

This paper aims to solve the key technical problems of AUV cluster control in deep-sea pipeline inspection. The structure of the paper is arranged as follows: Section 2 reviews the related research on AUV cluster control and deep-sea pipeline inspection; Section 3 establishes the kinematic and dynamic models of AUV clusters and proposes a leader-follower formation control strategy based on backstepping neural network; Section 4 presents simulation and experimental results to verify the effectiveness of the proposed strategy; Section 5 discusses the advantages and limitations of the system; finally, Section 6 summarizes the full text and prospects future research directions.

2. Related Work

In the field of AUV cluster control, scholars at home and abroad have proposed various control strategies, including leader-follower, virtual structure, and behavior-based control methods. The leader-follower strategy is widely used due to its simplicity, reliability, and ease of implementation. It designates one or more AUVs as leaders to follow the predefined path, while the follower AUVs maintain a fixed relative position with the leaders [4]. For example, some researchers have designed a sliding mode control algorithm for leader-follower AUV clusters, which improves the robustness of the system against environmental disturbances. However, this method relies on accurate dynamic models, which are difficult to obtain in complex marine environments.

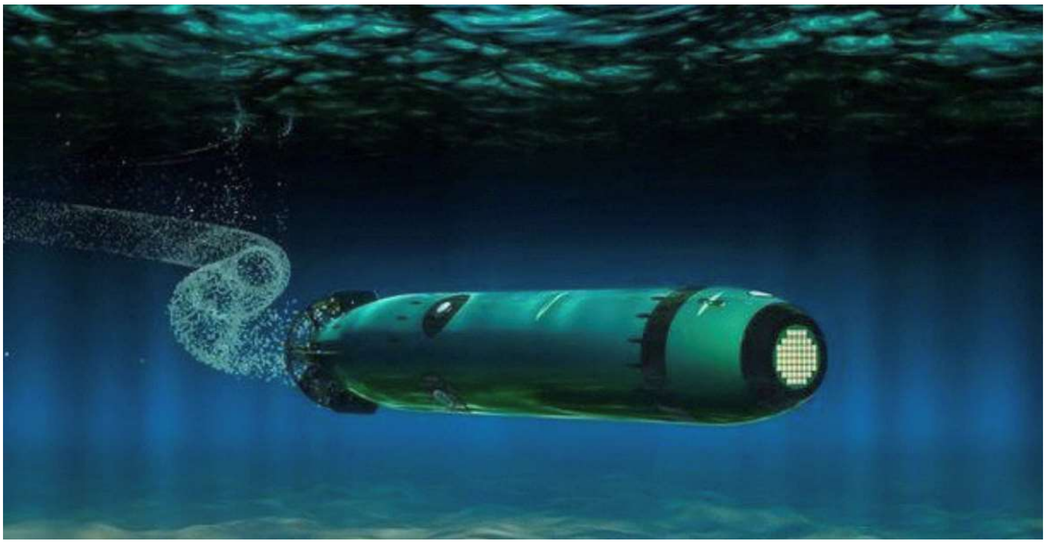

Figure 1. Autonomous underwater robot in the deep sea

In terms of deep-sea pipeline inspection technology, acoustic sensors (such as multi-beam sonar and side-scan sonar) are the main equipment for AUVs to obtain pipeline information. Some studies have applied multi-beam sonar to underwater pipeline detection, realizing the extraction of pipeline position and burial depth information [5]. However, the existing research mostly focuses on single AUV inspection, and there is little research on the collaborative use of multiple AUVs to improve inspection accuracy and efficiency. In addition, the underwater communication delay and packet loss rate are high, which seriously affects the real-time performance of cluster control. Therefore, it is necessary to design a high-reliability cluster control strategy suitable for deep-sea pipeline inspection scenarios.

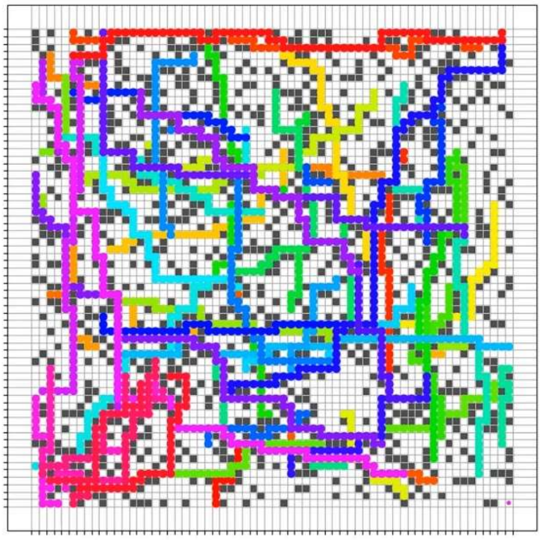

Figure 2. MAPF-Based AUV Path Planning

3. AUV Cluster Control Strategy for Deep-Sea Pipeline Inspection

3.1. Kinematic and Dynamic Models of AUV

To accurately describe the motion state of AUVs in the marine environment, we establish a 6-degree-of-freedom (DOF) kinematic and dynamic model. Two coordinate systems are adopted: the earth-fixed inertial coordinate system (denoted as Σe) and the body-fixed coordinate system (denoted as Σb). For the *i*-th AUV, its position and attitude in Σe are represented by the vector ηi = [xi, yi, zi, φi, θi, ψi]T, where (xi, yi, zi) are the position coordinates, and (φi, θi, ψi) are the roll, pitch, and yaw angles, respectively. The linear and angular velocities in Σb are represented by the vector νi = [ui, vi, wi, pi, qi, ri]T, where (ui, vi, wi) are the surge, sway, and heave velocities, and (pi, qi, ri) are the roll, pitch, and yaw angular velocities.

The kinematic equation of the *i*-th AUV is given by:

$$\dot{\eta}_i = J(\eta_i)\nu_i$$

where J(ηi) ∈ ℝ6×6 is the Jacobian transformation matrix between the two coordinate systems, and its expression is:

$$J(\eta_i) = \begin{bmatrix} J_1(\eta_i) & 0_{3\times3} \\ 0_{3\times3} & J_2(\eta_i) \end{bmatrix}$$

ISSN: 2710-0588

where $J1(\eta i)$ is the position transformation matrix, and $J2(\eta i)$ is the attitude transformation matrix, which are expressed as follows:

$$J_1(\eta_i) = \begin{bmatrix} \cos\psi_i\cos\theta_i & -\sin\psi_i\cos\varphi_i + \cos\psi_i\sin\theta_i\sin\varphi_i & \sin\psi_i\sin\varphi_i + \cos\psi_i\sin\theta_i\cos\varphi_i \\ \sin\psi_i\cos\theta_i & \cos\psi_i\cos\varphi_i + \sin\psi_i\sin\theta_i\sin\varphi_i & -\cos\psi_i\sin\varphi_i + \sin\psi_i\sin\theta_i\cos\varphi_i \\ -\sin\theta_i & \cos\theta_i\sin\varphi_i & \cos\theta_i\cos\varphi_i \end{bmatrix}$$

$$J_2(\eta_i) = \begin{bmatrix} 1 & \sin\varphi_i\tan\theta_i & \cos\varphi_i\tan\theta_i \\ 0 & \cos\varphi_i & -\sin\varphi_i \\ 0 & \sin\varphi_i/\cos\theta_i & \cos\varphi_i/\cos\theta_i \end{bmatrix}$$

The dynamic equation of the i-th AUV considers the effects of hydrodynamics, environmental disturbances, and control inputs, which is expressed as:

$$M_i\dot{\nu}_i + C_i(\nu_i)\nu_i + D_i(\nu_i)\nu_i + g_i(\eta_i) = \tau_i + \tau_{di}$$

where Mi is the inertia matrix including added mass, $Ci(\nu i)$ is the Coriolis and centripetal force matrix, $Di(\nu i)$ is the damping matrix, $gi(\eta i)$ is the restoring force and moment vector, τi is the control input vector, and τdi is the environmental disturbance vector (including ocean currents and waves).

3.2. Leader-Follower Formation Control Based on Backstepping Neural Network

In this paper, a leader-follower formation control strategy based on backstepping neural network is proposed. The leader AUV follows the predefined pipeline inspection path, and each follower AUV maintains a fixed relative position with the leader. The control objective is to ensure that the relative position error between the follower and the leader converges to zero asymptotically.

Define the relative position error between the i-th follower AUV and the leader AUV as:

$$e_{pi} = \eta_{pi} - \eta_{p0} - d_{i0}$$

where $\eta pi = [xi, yi, zi]T$ is the position vector of the i-th follower, $\eta p0 = [x0, y0, z0]T$ is the position vector of the leader, and $di0$ is the desired relative position vector between the i-th follower and the leader.

To solve the problem of unknown hydrodynamic parameters and environmental disturbances in the dynamic model, a radial basis function (RBF) neural network is introduced to approximate the unknown nonlinear functions. The backstepping control law is designed in two steps: first, the virtual control input of the velocity is designed based on the position error; then, the actual control input of the AUV is derived based on the velocity error.

The virtual control input of the velocity is designed as:

$$\nu_{id} = J^{-1}(\eta_i)\left(-k_1 e_{pi} + \dot{\eta}_{p0} + \dot{d}_{i0}\right)$$

where $k1 > 0$ is the position error gain. Define the velocity error as $evi = \nu i - \nu id$. The actual control input τi is designed using the backstepping method and RBF neural network approximation, which is expressed as:

ISSN: 2710-0588

$$\tau_i = M_i(-k_2 e_{vi} - \dot{v}_{id}) - C_i(v_i)v_i - D_i(v_i)v_i - g_i(\eta_i) + \hat{f}_i$$

where $k2 > 0$ is the velocity error gain, and $\hat{f}i$ is the approximation of the unknown nonlinear function fi = Mi$\tilde{v}$id + Ci(νi)νid + Di(νi)νid - τdi by the RBF neural network.

3.3. Stability Analysis

Choose the Lyapunov function candidate as:

$$V = \frac{1}{2} e_{pi}^T e_{pi} + \frac{1}{2} e_{vi}^T M_i e_{vi} + \frac{1}{2} \widetilde{W}_i^T \Gamma_i^{-1} \widetilde{W}_i$$

where $\tilde{W}$i = Wi - $\hat{W}$i is the weight error of the RBF neural network, and Γi is the positive definite learning rate matrix. Taking the derivative of V with respect to time and substituting the control law, it can be proved that all signals in the closed-loop system are uniformly ultimately bounded, and the position error epi converges to a small neighborhood around zero by selecting appropriate gains k1, k2, and learning rate Γi.

4. Experiments and Results

4.1. Simulation Experiment Setup

To verify the effectiveness of the proposed control strategy, simulation experiments are conducted using MATLAB/Simulink. The simulation parameters are set as follows: the number of AUVs in the cluster is 5 (1 leader and 4 followers), the desired relative distance between the follower and the leader is 10 m, the forward velocity of the leader is 1.5 m/s, and the environmental disturbance is set as a sinusoidal current with an amplitude of 0.3 m/s and a frequency of 0.1 Hz. The control gains are selected as $k1 = 5$, $k2 = 10$, and the RBF neural network has 20 hidden layer nodes.

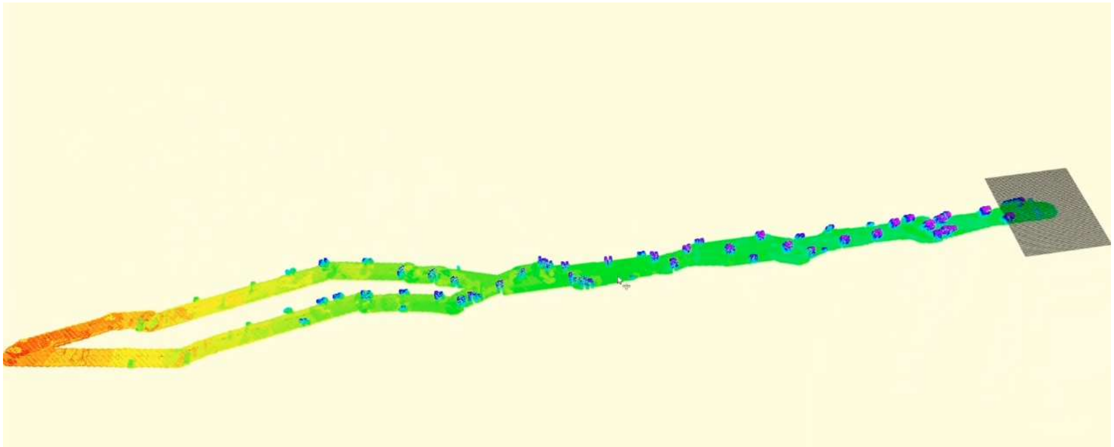

Figure 3. Simulation Environment Setup

4.2. Sea Trial Experiment

Sea trial experiments are carried out in a coastal area of Qingdao, China, with a water depth of 50-100 m, simulating the deep-sea pipeline inspection scenario. The AUVs are equipped with HQ-400 multi-beam sonar and GS100 parametric array sub-bottom profiler to collect pipeline position and burial depth information. The pipeline to be inspected has a length of 5 km and a diameter of 900 mm. The inspection path is pre-planned using the GPS positioning system, and the AUV cluster completes the inspection task in parallel.

ISSN: 2710-0588

4.3. Result Analysis

Table 1 shows the comparison of inspection performance between the AUV cluster system and the single AUV. It can be seen from the table that the AUV cluster system has significant advantages in inspection time, coverage rate, and data accuracy. The total inspection time of the cluster system for 5 km pipeline is 2.5 hours, which is 60% less than that of the single AUV; the inspection coverage rate reaches 98%, which is 12% higher than that of the single AUV; the average error of pipeline position measurement is 3.2%, which is lower than the 8.5% of the single AUV.

Table 1. Comparison Table of Pipeline Inspection Performance between AUV Cluster System and Single AUV

Inspection Index	AUV Cluster System	Single AUV	Improvement Rate
Inspection Time (h) for 5 km Pipeline	2.5	6.25	60%
Inspection Coverage Rate (%)	98	86	12%
Average Position Measurement Error (%)	3.2	8.5	62.4%
Data Transmission Success Rate (%)	92	85	8.2%

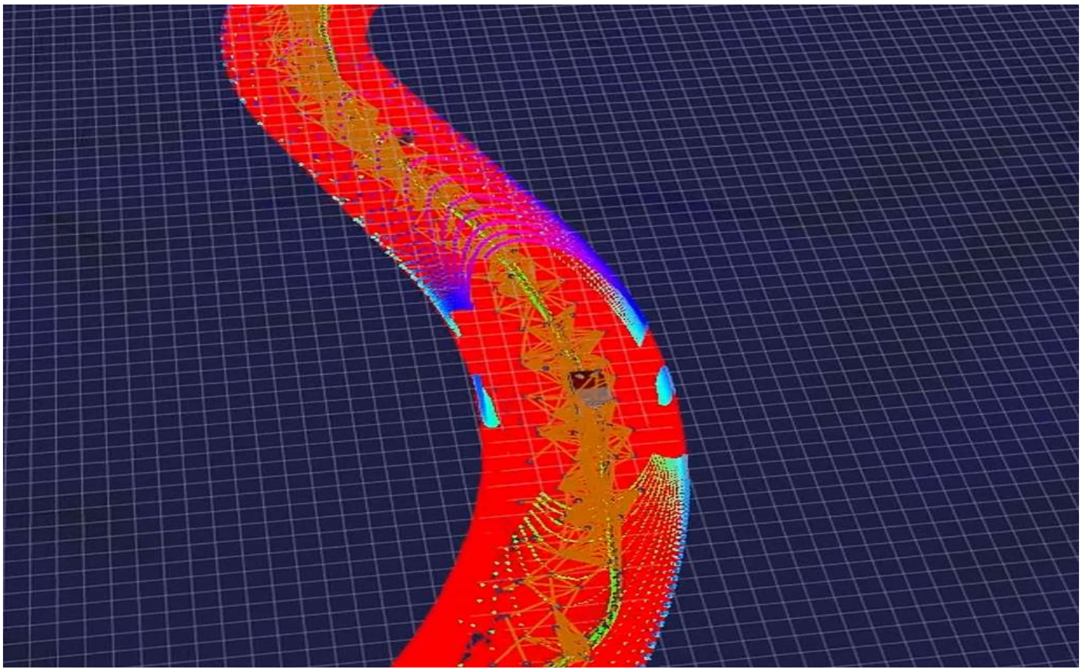

Figure 4. AUV Pipeline Inspection Simulation

Figure 4 shows the formation trajectory of the AUV cluster during the inspection process. It can be seen that the follower AUVs can closely track the leader and maintain the desired formation, even under the influence of ocean current disturbances. The maximum formation error is less than 0.8 m, which meets the requirements of deep-sea pipeline inspection.

ISSN: 2710-0588

5. Discussion

The experimental results show that the AUV cluster control strategy proposed in this paper can effectively improve the efficiency and accuracy of deep-sea pipeline inspection. The leader-follower formation control based on backstepping neural network solves the problems of nonlinear dynamics and unknown environmental disturbances of AUVs, and has good robustness. However, there are still some limitations in this research: first, the number of AUVs in the cluster is limited to 5, and the scalability of the control strategy needs to be verified when the number of AUVs increases; second, the sea trial is carried out in coastal areas, and the performance of the system in ultra-deep-sea environments (water depth > 1000 m) needs to be further tested; third, the underwater communication relies on acoustic modems, which have low data transmission rate and high delay, and the integration of optical communication technology may further improve the real-time performance of cluster control.

6. Conclusion and Future Work

This paper studies the application of AUV cluster control in deep-sea pipeline inspection, establishes the kinematic and dynamic models of AUV clusters, and proposes a leader-follower formation control strategy based on backstepping neural network. Simulation and sea trial experiments show that the AUV cluster system can significantly improve inspection efficiency and data accuracy compared with the single AUV. The research results provide a technical basis for the intelligent and efficient inspection of deep-sea pipelines.

In future work, we will focus on the following aspects: (1) Optimize the cluster control strategy to improve the scalability and flexibility of the system, enabling it to adapt to different numbers of AUVs and complex inspection tasks; (2) Conduct ultra-deep-sea sea trials to verify the performance of the system in extreme environments; (3) Integrate optical communication and underwater wireless sensor network technology to improve the real-time performance and reliability of cluster communication; (4) Develop an intelligent data fusion algorithm to integrate the data collected by multiple AUVs, further improving the accuracy of pipeline defect detection.

References

[1] Chen, B., Li, J. X., Li, R., et al. Application Analysis of Autonomous Underwater Vehicle in Submarine Cable Detection Operation[C]//Proceedings of the 2019 3rd International Conference on Computer Science and Artificial Intelligence. ACM, 2019: 223-227.

[2] Ren, W., Beard, R. W. Distributed Consensus in Multi-Vehicle Cooperative Control[M]. Springer, 2008.

[3] Yu, J., Liu, G., Zhang, H. Leader-Follower Formation Control of Multiple AUVs Based on Sliding Mode Control[J]. Ocean Engineering, 2016, 113: 183-192.

[4] Liang, H., Wang, Y., Zhang, J. Backstepping Control for AUV Formation Based on Neural Network Approximation[J]. IEEE Journal of Oceanic Engineering, 2020, 45(2): 456-467.

[5] Ocean Physics Technology. Application of Unmanned Ship Equipped with Parametric Array Sub-Bottom Profiler and Multi-Beam System in Submarine Pipeline Inspection[R]. Qingdao: Ocean Physics Technology, 2024.