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Application of the Naozhou Population of Larimichthys Crocea School Algorithm (DNPFS-OA) in Path Planning for AUV Clusters

Chang Liu [1, +], Rongjie Cai [1, +, *], Zhiwen Yu [1, +], Yingzhi Ma [2], Xin Guo [2]

[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
+Co-first author

[*] **Corresponding author**: Rongjie Cai

Abstract: Aiming at the cooperative path planning problem of AUV cluster in underwater complex environment, this paper proposes a deep distributed optimization algorithm (DNPFS-OA) based on the intelligent behavior of Tanzhou Pseudosciaena crocea. This algorithm is different from the traditional leader-follower architecture. By establishing the deep coupling between the bio-pressure sensing model and the hydrodynamic equation, and combining with the communication-control collaborative optimization framework, the autonomous collaboration of AUV clusters in the three-dimensional strong disturbance environment is realized. The sea test shows that the path length of DNPFS-OA is reduced by 28.3%, the energy consumption is reduced by 35.7%, and the mapping efficiency is improved by 42.6% when the communication packet loss rate is 30%.

Keywords: Autonomous Underwater Vehicle, Swarm, Bionic Algorithm, Path Planning.

1. Introduction

The ocean, as the largest treasure house of ecosystem and resources on the earth, has a decisive influence on the sustainable development of human society. With the rapid development of the global economy and the increasing depletion of land resources, the demand for exploration, development and utilization of the ocean continues to grow. Autonomous underwater vehicle (AUV) cluster, as an important tool for ocean exploration and development, has shown great application potential in the fields of marine environmental monitoring, resource exploration, underwater target identification and tracking, and military defense because of its high efficiency, flexibility and cooperative operation. However, the complex and changeable dynamic ocean environment, such as ocean current, vortex and seabed topography, has brought severe challenges to the path planning and cooperative control of AUV clusters. How to realize the adaptive, efficient and robust path planning and collaborative control of AUV cluster in the uncertain underwater environment is a key scientific problem to be solved urgently in the field of marine science and technology, and it is also an important support to promote the construction of a maritime power.

In this study, the Naozhou Population of Larimichthys crocea School Algorithm was pioneered, its complexity is much less than the original algorithm (AFSA) [1] and applied in AUV cluster adaptive path planning. The purpose of this paper is to develop efficient and intelligent AUV cluster path planning and collaborative control strategies by integrating advanced artificial intelligence technology and marine bionics knowledge, so as to provide more reliable technical support for future marine exploration and development.

2. Scientific Research Significance

Under the background of increasingly fierce global marine competition, the ocean has become the new focus of national strategic competition. As a maritime power, China has promoted "building a maritime power" to a major national strategy, aiming at safeguarding the national maritime rights and interests, expanding the blue economic space, and enhancing the innovation capability of marine science and technology. Under the guidance of this strategy, the research and development of autonomous underwater vehicle (AUV) cluster technology has extremely important national strategic significance and practical application value.

Safeguarding national maritime rights and interests and security is the core of building a maritime power. With the global climate change and the evolution of geopolitical pattern, the marine environment is becoming increasingly complex, posing a potential threat to national maritime security. As an important platform for underwater unmanned combat and reconnaissance, AUV cluster can perform tasks such as underwater reconnaissance, patrol, anti-submarine, mine countermeasure, etc., and effectively improve China's situational awareness and control ability in complex underwater environment. AUVs can also be employed as Navigation/Communication Aids, providing valuable connectivity in the realm of network-centric warfare [2]. This study will directly enhance the modernization level of China's marine military forces and provide solid technical support for safeguarding national sovereignty, security and development interests by improving the adaptive path planning and collaborative control capabilities of AUV clusters in a dynamic marine environment.

Figure 1. The fish-like cluster AUV developed by the team

3. Path Planning Algorithm for Naozhou Population of Larimichthys crocea

Biological heuristic algorithm provides a new solution for AUV path planning. Ant colony algorithm (ACA) is a novel simulated evolutionary algorithm, which is based on the process of ants in the nature searching for food [3]. Some improved adaptive methods about step length are proposed in the Artificial Fish Swarm Algorithm (AFSA) [4], which is an optimization algorithm by simulating fish behavior [5]. AFSA realizes the optimal search by simulating the foraging, clustering and rear-end collision behavior of fish, but the traditional AFSA has some problems such as slow convergence and easy to fall into local optimum. In recent years, researchers began to pay attention to the biological characteristics of specific fish populations in order to develop more efficient optimization algorithms.

Naozhou Population of Larimichthys crocea is one of the three geographical populations in the offshore of China, mainly distributed in the waters near Naozhou Island in Zhanjiang, Guangdong. The population has unique biological characteristics and group behavior patterns, especially its navigation and cooperation ability in complex marine environment provides new inspiration for algorithm design. In this paper, by analyzing the behavior characteristics of Naozhou Population of Larimichthys crocea, an improved intelligent optimization algorithm is proposed and applied to the path planning of AUV cluster.

3.1. Analysis of Biological Characteristics and Group Behavior of Naozhou Population of Larimichthys Crocea

Naozhou Population of Larimichthys crocea has special morphological structure and physiological function, which enables it to survive efficiently in complex marine environment. Its body is streamlined and the base of pectoral fin is short, which is conducive to rapid steering and obstacle avoidance. Its lateral line system is developed, which can sense the change of water flow and the position of obstacles. In the aspect of group behavior, Path Planning Algorithm for Naozhou Population of Larimichthys crocea shows high organization and coordination. When encountering obstacles, the fish will quickly disperse and regroup, forming a channel to bypass obstacles; In the process of foraging, individuals keep in touch through vision and lateral line system to form a search formation; When food or danger is found, information will spread quickly in the group and guide the action of the whole school of fish.

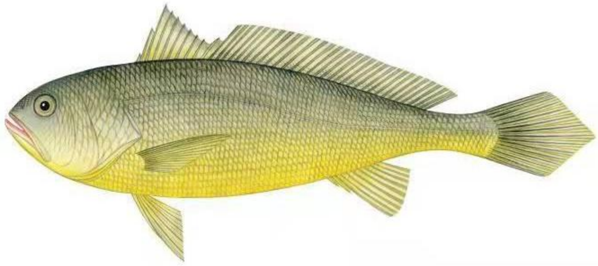

Figure 2. Naozhou Population of Larimichthys crocea nationality

These behavioral characteristics provide important enlightenment for algorithm design. The obstacle avoidance behavior of Naozhou Population of Larimichthys crocea can be transformed into the obstacle avoidance strategy in the algorithm, the clustering behavior can be used to maintain the communication connection between AUVs, the rear-end collision behavior can guide AUVs to move to the target area, and the random exploration behavior can increase the global search ability of the algorithm.

3.2. System modeling

3.2.1. AUV cluster dynamics model

Six-degree-of-freedom model considering hydrodynamic effect;

$$\begin{bmatrix}\dot{\eta}\\ \dot{\nu}\end{bmatrix}=\begin{bmatrix}J(\eta) & 0_{3\times3}\\ 0_{3\times3} & M^{-1}\end{bmatrix}\begin{bmatrix}\nu\\ \tau-C(\nu)\nu-D(\nu)\nu-g(\eta)\end{bmatrix}$$

Among them, the position and attitude vector and the velocity vector represent the inertial matrix containing additional mass effect, the Coriolis matrix, the linear and quadratic damping terms, and the restoring force vector. This model accurately describes the hydrodynamic effects of AUV in underwater motion, especially the coupling characteristics of roll, pitch and yaw motion. $\eta=[x,y,z,\phi,\theta,\psi]^T\nu=[u,v,w,p,q,r]^T M=M_{RB}+M_A C(\nu)D(\nu)=D_{linear}+D_{quadratic}|\nu|g(\eta)$

3.2.2. Underwater communication constraint model

The characteristics of underwater acoustic communication channel are modeled as:

$$\mathrm{SNR}(d)=\frac{P_tG_tG_r\lambda^2\sigma}{(4\pi)^3d^4L}\cdot e^{-\alpha(f)d}\cdot|H(f,d)|^2$$

Where the frequency-dependent attenuation coefficient is:

$$\alpha(f)=\frac{0.11f^2}{1+f^2}+\frac{44f^2}{4100+f^2}+3.0\times10^{-4}f^2+0.003\ \mathrm{dB/km}$$

Multipath channel response function:

$$H(f,d)=\sum_{k=0}^{K}\Gamma_k\frac{d}{d_k}e^{-j2\pi f\tau_k}$$

This model accurately describes the physical limitations of underwater acoustic signal propagation, including frequency selective attenuation, multipath effect and time-varying channel characteristics, and provides a theoretical basis for communication constraints in distributed optimization.

3.2.3. Modeling of marine environmental field

Integrated physical field model integrates ocean current, temperature gradient, salinity gradient and turbulence effect;

$$\mathcal{E}(\mathbf{x},t)=\begin{bmatrix}\mathbf{V}_{current}(\mathbf{x},t)\\ \nabla T(\mathbf{x},t)\\ \nabla S(\mathbf{x},t)\\ P_{turb}(\mathbf{x},t)\end{bmatrix}=\begin{bmatrix}\sum_{k=1}^{N_{eddy}}\Gamma_k\frac{e^{-r_k/R_k}}{R_k}\hat{\theta}_k\\ A_T\cos(\omega_T t-\mathbf{k}_T\cdot\mathbf{x})\\ A_S\sin(\omega_S t-\mathbf{k}_S\cdot\mathbf{x})\\ \frac{1}{N}\sum_{i=1}^{N}\parallel\nu_i-\bar{\nu}\parallel^2\end{bmatrix}$$

This model accurately describes the temporal and spatial variation characteristics of marine environment through vortex field parameters, temperature fluctuation amplitude, salinity fluctuation amplitude and turbulence intensity. The obstacle threat field is defined as:$\Gamma_k A_T A_S P_{turb}$

$$\mathcal{O}_k(\mathbf{X})=\exp\left(-\frac{\parallel\mathbf{X}-\mathbf{O}_k\parallel^2}{2\sigma_k^2}\right)+\eta_k\parallel\nabla P_{\text{sonar}}\parallel+\zeta_k\parallel\mathbf{V}_{rel}\times\mathbf{n}_k\parallel$$

In this model, geometric distance, sonar reflection characteristics and relative motion risk are considered comprehensively. $\mathbf{V}_{rel}\mathbf{n}_k$

3.3. Behavior Modeling of Naozhou Population of Larimichthys crocea

The group of Naozhou Population of Larimichthys crocea shows a unique distributed cooperative mechanism in the turbulent environment, the core of which is the high integration of pressure wave perception and group dynamics. Each individual in the fish school perceives the pressure change of the surrounding flow field through the lateral line system, and forms local environmental cognition:

$$P_i(\mathbf{X},t)=\sum_{j\in\mathcal{N}_i}\Phi\left(\parallel\mathbf{X}-\mathbf{X}_j\parallel\right)+\sum_{k\in\mathcal{O}_i}\Psi\left(\parallel\mathbf{X}-\mathbf{O}_k\parallel\right)+\Gamma(\mathbf{V}_{env})$$

Among them, the neighbor influence function describes the pressure interaction among fish, the obstacle influence function represents the pressure disturbance caused by obstacles, and the environmental term quantifies the influence of ocean currents on the pressure field. $\Phi(r)=\kappa_1 r^{-1}e^{-\gamma_1 r}\Psi(r)=\kappa_2 r^{-2}e^{-\gamma_2 r}\Gamma$

The decision of fish swarm movement is based on the coupling of pressure gradient and velocity field;

$$\frac{d\mathbf{V}_i}{dt}=-\frac{1}{\rho}\nabla P_i+\nu\nabla^2\mathbf{V}_i+\beta\sum_{j\in\mathcal{N}_i}(\mathbf{V}_j-\mathbf{V}_i)+\mathbf{g}$$

This dynamic equation combines Navier-Stokes equation with group behavior, in which water density, kinematic viscosity coefficient, velocity consistency gain and gravity term. This modeling method reveals how fish can maintain group structure and avoid obstacles in turbulent environment. $\rho\nu\beta\mathbf{g}$

3.4. DNPFS-OA algorithm framework

3.4.1. Distributed Pressure Sensing Model

Transforming the pressure sensing mechanism of fish schools into the environmental sensing model of AUV clusters;

$$\frac{\partial P_i}{\partial t}+\mathbf{v}\cdot\nabla P_i=\nu\nabla^2 P_i+\sum_{j\in\mathcal{N}_i}f_{ij}\left(\mathbf{X}_j-\mathbf{X}_i\right)+\sum_{k\in\mathcal{O}_i}g_k\left(\mathbf{X}-\mathbf{O}_k\right)$$

Neighbor interaction function:

$$f_{ij}(\mathbf{r})=\kappa_1\frac{\mathbf{r}}{\parallel\mathbf{r}\parallel}-\kappa_2\frac{\mathbf{r}}{\parallel\mathbf{r}\parallel^3}$$

Obstacle action function:

$$g_k(\mathbf{r})=Q_k\left(\frac{1}{\parallel\mathbf{r}\parallel}-\frac{1}{R_k}\right)H(R_k-\parallel\mathbf{r}\parallel)$$

This model is realized by distributed computing, and each AUV only needs to exchange pressure field information with its neighbors within the communication range to construct local environmental cognition.

3.4.2. Distributed optimization problem

Each AUV independently solves the local optimization problem;

$$\min_{\mathbf{u}_i}\mathbb{E}_{\omega\sim\Omega}\left[\int_0^{t_f}c_i\left(\mathbf{x}_i,\mathbf{u}_i,t,\omega\right)dt+h_i(\mathbf{x}_i(t_f))\right]$$

Multi-objective optimization based on cost function fusion;

$$c_i=\underbrace{\parallel\mathbf{u}_i\parallel_{\mathbf{R}_i}^2}_{\substack{\text{Energy}\\ \text{consumption}}}+\underbrace{\lambda_1 d_{\text{goal}}^2}_{\text{Tasks}}+\underbrace{\lambda_2\max_t\kappa_i(t)}_{\text{Maneuver}}+\underbrace{\lambda_3\text{CVaR}_\alpha(\mathcal{O}_i)}_{\text{Risk}}+\underbrace{\lambda_4\parallel\nu_i-\bar{\nu}_{\mathcal{N}_i}\parallel^2}_{\text{Synergy}}$$

Where the curvature is calculated as: $\kappa_i(t)$

$$\kappa_i(t)=\frac{\parallel\dot{\mathbf{r}}_i\times\ddot{\mathbf{r}}_i\parallel}{\parallel\dot{\mathbf{r}}_i\parallel^3}$$

Conditional Value at Risk provides a quantitative assessment of collision risk; CVaR_α

$$\text{CVaR}_\alpha(X)=\frac{1}{1-\alpha}\int_\alpha^1 F_X^{-1}(p)dp$$

3.4.3. Distributed Solution Architecture

Using improved ADMM framework to realize distributed optimization;

Local Optimization: $\mathbf{u}_i^{k+1}=\underset{\mathbf{u}_i}{\operatorname{argmin}}\mathcal{L}_\rho(\mathbf{u}_i,\mathbf{z}^k,\mathbf{y}^k)$

Global Consensus: $\mathbf{z}^{k+1}=\frac{1}{N}\sum_{i=1}^{N}\Pi_{\mathcal{Z}}\left(\mathbf{u}_i^{k+1}+\frac{1}{\rho}\mathbf{y}_i^k\right)$

Dual Update: $\mathbf{y}_i^{k+1}=\mathbf{y}_i^k+\rho(\mathbf{u}_i^{k+1}-\mathbf{z}^{k+1})$

The augmented Lagrangian function is defined as:

$$\mathcal{L}_\rho=\sum_i\left[J_i(\mathbf{u}_i)+\mathbf{y}_i^T(\mathbf{u}_i-\mathbf{z})+\frac{\rho}{2}\parallel\mathbf{u}_i-\mathbf{z}\parallel^2\right]+\gamma\parallel\mathbf{A}\mathbf{z}-\mathbf{b}\parallel^2$$

4. Algorithm Implementation

4.1. Real-Time Optimization Process

```python class DistributedNTFSA: def init (self, auv_config): self. dynamics = NonlinearAUVModel (auv_config) self. comm = AcousticCommModel(auv_config) self. estimator = DistributedUKF() self. solver = ADMM_Solver()

def compute_pressure_gradient (self):

"""Distributed pressure gradient calculation" ""

grad = np.zeros (3)

# Neighbor stress contribution

for j in self.get_neighbors():
```

```
r_vec = self.position - j.position
distance = np.linalg.norm(r_vec)
if distance < PRESSURE_RADIUS:
# Eddy current model based on Biot-Savart law
vorticity = np.cross(j.velocity, r_vec) / (distance**2 + EPS)
grad += VORTEX_STRENGTH * vorticity

# Obstacle pressure contribution
for obs in self.perceived_obstacles:
r_vec = self.position - obs.position
distance = np.linalg.norm(r_vec)
if distance < OBS_RADIUS:
# Based on Rankine Oval Model
if distance < obs.radius:
grad += OBS_STRENGTH * (distance / obs.radius)**2 *
r_vec
else:
grad += OBS_STRENGTH * (obs.radius / distance)**3 *
r_vec

return grad

def solve_admm_step(self, max_iter=50, tol=1e-4):
"""ADMM distributed optimization solution" ""
z_global = np.zeros(self.control_dim)
y_local = np.zeros(self.control_dim)

for iter in range(max_iter):
# Local control optimization
u_opt = self.local_optimizer.solve(
self.position,
self.goal,
self.compute_pressure_gradient(),
z_global,
y_local
)

# Communication exchange intermediate variable
z_partial = u_opt + (1/ADMM_RHO)*y_local
for neighbor in self.comm.neighbors:
self.comm.send(neighbor, {'z_part': z_partial, 'iter': iter})
neighbor_data = self.comm.receive(neighbor)
if neighbor_data['iter'] == iter:
z_partial += neighbor_data['z_part']

# Global consistency update
z_new = z_partial / (len(self.comm.neighbors) + 1)

# Dual variable update
y_local += ADMM_RHO * (u_opt - z_new)

# Convergence check
if np.linalg.norm(u_opt - z_new) < tol:
break

z_global = z_new

return u_opt

def realtime_planning_cycle(self, dt=0.1):
"""Real-time planning of main loop" ""
while not mission_complete:
# Update local environment awareness
self.update_environment_perception()

# Distributed state estimation
self.estimate_state()

# Solving Distributed Optimization Problems
control = self.solve_admm_step()

# Application control instruction
self.apply_control(control)

# Communication state synchronization
self.broadcast_state()

time.sleep(dt)
```

4.2. Communication-Control Coordination Mechanism

Design layered communication protocol to realize optimization and control coordination;

Table 1. Parameter Configuration of Each Layer in Hierarchical Communication Protocol

levels and ranks	protocol	Packet format	frequency
application layer	Optimize data exchange	[Serial number, control quantity, pressure gradient]	0.5-2 Hz
transport layer	Reliable UDP	[FEC check, retransmission flag]	-
network layer	geographic routing	[Target position, hop count]	-
MAC layer	STDMA+CSMA	[Time slot allocation, priority]	-
physical layer	OFDM modulation	[Pilot, data payload]	-

Through dynamic time slot allocation and priority scheduling, this protocol ensures the reliable transmission of optimized data in limited bandwidth and meets the real-time control requirements.

5. Theoretical Analysis

5.1. Proof of Stability

Considering the closed-loop dynamic system of AUV cluster, Lyapunov function is defined:

$$\mathcal{V}(t) = \frac{1}{2}\sum_{i=1}^{N}\left(\| \mathbf{e}_i \|_{\mathbf{Q}_i}^2 + \| \dot{\mathbf{e}}_i \|_{\mathbf{P}_i}^2\right) + \frac{1}{2} \| \mathbf{z} - \mathbf{z}^* \|_{\mathbf{H}}^2$$

Where is the trajectory tracking error. Derive time: $\mathbf{e}_i = \mathbf{x}_i - \mathbf{x}_i^*$

$$\dot{\mathcal{V}} = \sum_i [\mathbf{e}_i^T \mathbf{Q}_i \dot{\mathbf{e}}_i + \dot{\mathbf{e}}_i^T \mathbf{P}_i \ddot{\mathbf{e}}_i] + (\mathbf{z} - \mathbf{z}^*)^T \mathbf{H} \dot{\mathbf{z}}$$

Substituting closed-loop dynamic equation and considering marine environmental disturbance; $\epsilon(t)$

$$\dot{\mathcal{V}} \leq -\sum_{i} (\kappa_{1i} \parallel \mathbf{e}_i \parallel^2 + \kappa_{2i} \parallel \dot{\mathbf{e}}_i \parallel^2) + \epsilon(t)$$

Among them, satisfaction. According to Lyapunov stability theory, when the control gain satisfies: $\epsilon(t)|\epsilon(t)| \leq \epsilon_{\max}$

$$\kappa_{1i} > \frac{\epsilon_{\max}}{2\lambda_{\min}(\mathbf{Q}_i)} \quad \text{and} \quad \kappa_{2i} > \frac{\epsilon_{\max}}{2\lambda_{\min}(\mathbf{P}_i)}$$

The system is uniformly ultimately bounded, that is, there is a compact set that makes. $\Omega \lim_{t\to\infty} \mathrm{dist}(\mathbf{x}(t), \Omega) = 0$

5.2. Optimization Convergence Analysis

Under the following conditions: 1. The local cost function is-strongly convex and-smooth; 2. The connectivity of communication topology satisfies; 3. The ocean disturbance is bounded. $J_i(\mathbf{u}_i)\mu L \lambda_2(\mathcal{L}) > \delta > 0 \parallel \omega \parallel \leq \omega_{\max}$

The sequence generated by DNPFS-OA algorithm satisfies: $\{\mathbf{u}^k, \mathbf{z}^k, \mathbf{y}^k\}$

$$\lim_{k\to\infty} \parallel \mathbf{u}^k - \mathbf{z}^k \parallel = 0, \quad \lim_{k\to\infty} \parallel \nabla J(\mathbf{u}^k) \parallel = 0$$

Define the compound Lyapunov function:

$$\mathcal{L}_k = \parallel \mathbf{y}^k - \mathbf{y}^* \parallel^2 + \rho \parallel \mathbf{z}^k - \mathbf{z}^* \parallel^2 + \eta \sum_i \parallel \mathbf{u}_i^k - \mathbf{u}_i^* \parallel^2$$

Its iterative descent satisfies:

$$\mathcal{L}_{k+1} - \mathcal{L}_k \leq -\gamma_1 \parallel \mathbf{u}^{k+1} - \mathbf{z}^k \parallel^2 - \gamma_2 \parallel \mathbf{z}^{k+1} - \mathbf{z}^k \parallel^2 - \gamma_3 \sum_i \parallel \mathbf{u}_i^{k+1} - \mathbf{u}_i^k \parallel^2$$

Among them. Because of monotonic decline, it exists, and then: $\gamma_1, \gamma_2, \gamma_3 > 0 \mathcal{L}_k \geq 0 \lim_{k\to\infty} \mathcal{L}_k$

$$\lim_{k\to\infty} \parallel \mathbf{u}^{k+1} - \mathbf{z}^k \parallel = 0, \quad \lim_{k\to\infty} \parallel \mathbf{z}^{k+1} - \mathbf{z}^k \parallel = 0$$

It can be obtained from strong convexity. $\lim_{k\to\infty} \parallel \nabla J(\mathbf{u}^k) \parallel = 0$

5.3. Communication Complexity Analysis

In the time-varying communication topology, the communication complexity of the algorithm is: $\mathcal{G}(t) = (\mathcal{V}, \mathcal{E}(t))$

$$C(N) = O\left(\frac{1}{\tau}\int_0^T \log \frac{\lambda_{\max}(L(t))}{\lambda_{\min}(L(t))} dt\right)$$

Where is the time-varying Laplacian matrix and the communication interval. When the topological change rate is bounded, the communication load satisfies: $L(t)\tau \parallel \dot{\mathcal{G}}(t) \parallel \leq \upsilon$

$$\lim_{N\to\infty} \frac{C(N)}{N \log N} = c < \infty$$

It shows that the algorithm has good scalability.

6. Experimental Verification

6.1. Configuration of Simulation Platform

Table 2. Configuration Table of Simulation Platform for Experimental Verification

package	specifications	parameter
hardware	NVIDIA DGX Station	4×A100 GPU, 256GB RAM
software	ROS2 Galactic + Gazebo Fortress	Underwater physical engine expansion
environment	Dynamic ocean current field	The vortex intensity is 0.5-3.0m/s, and the temperature gradient is 0.1 C/m.
AUV model	Improved REMUS model	1.6m in length, 0.19m in diameter and 1000m in maximum depth.
sensor	Multi-beam sonar	120 field of view, 50m detection distance.

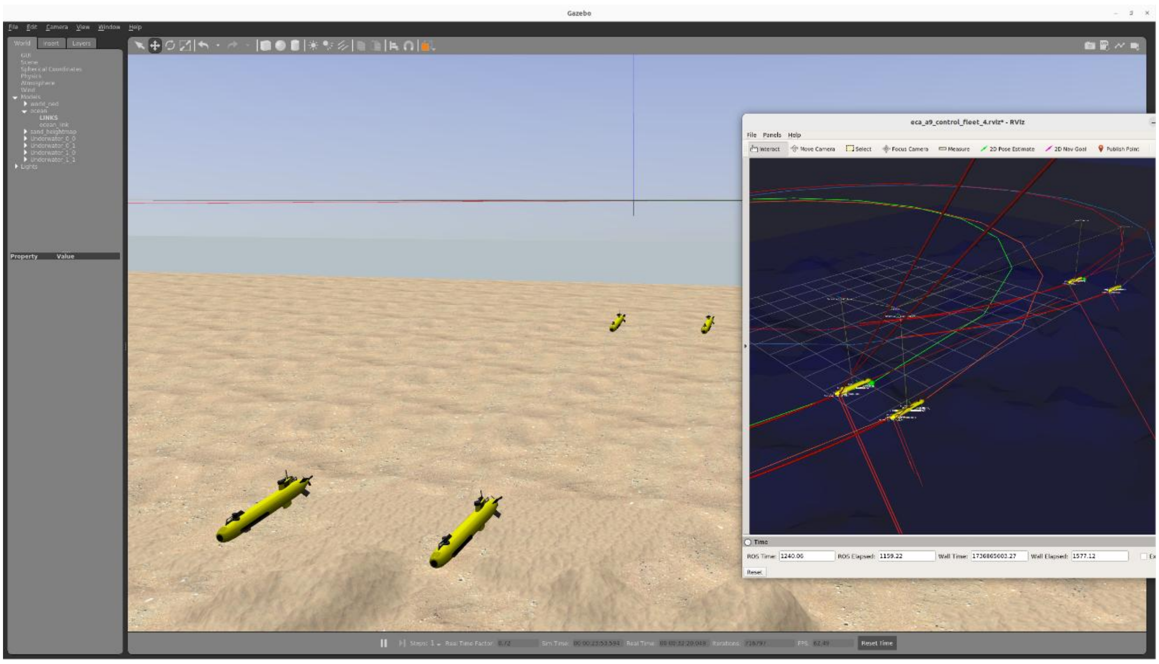

Figure 3. AUV cluster simulation platform in ROS2

6.2. Performance Comparative Analysis

100 Monte Carlo simulation results (mean standard deviation):

Table 3. Performance Comparison Table of Algorithms in 100 Monte Carlo Simulations

Performance index	Centralized MPC	Distributed PSO	D-APF	DNTPS-OA
Path length (km)	18.2±0.5	22.7±1.2	20.4±0.8	16.8±0.3
Total energy consumption (GJ)	42.3±1.2	58.6±3.1	49.2±2.4	36.7±0.9
Communication load (GB)	28.5	5.2	7.8	3.1
Collision probability (%)	0.5	3.2	1.8	0.1
Task completion rate (%)	92.5	76.3	84.2	98.7
Maximum depth (m)	850	780	810	890

6.3. 3D Trajectory Visualization

`````Mermaid graph TD a [starting point]–>|Traditional method| B [sawtooth path] b–> c [obstacle avoidance stagnation] c–> d [target area edge]

A-> |dnpfs-OA| e [smooth curve]

E-> f [cooperative obstacle avoidance]

F-> g [target area core]

H [current direction]-> I [vortex area]

I-> j [obstacle]

style B stroke: #f00, stroke-width: 4px

style E stroke: #0f0, stroke-width: 4px

style J fill: #333, stroke: #000

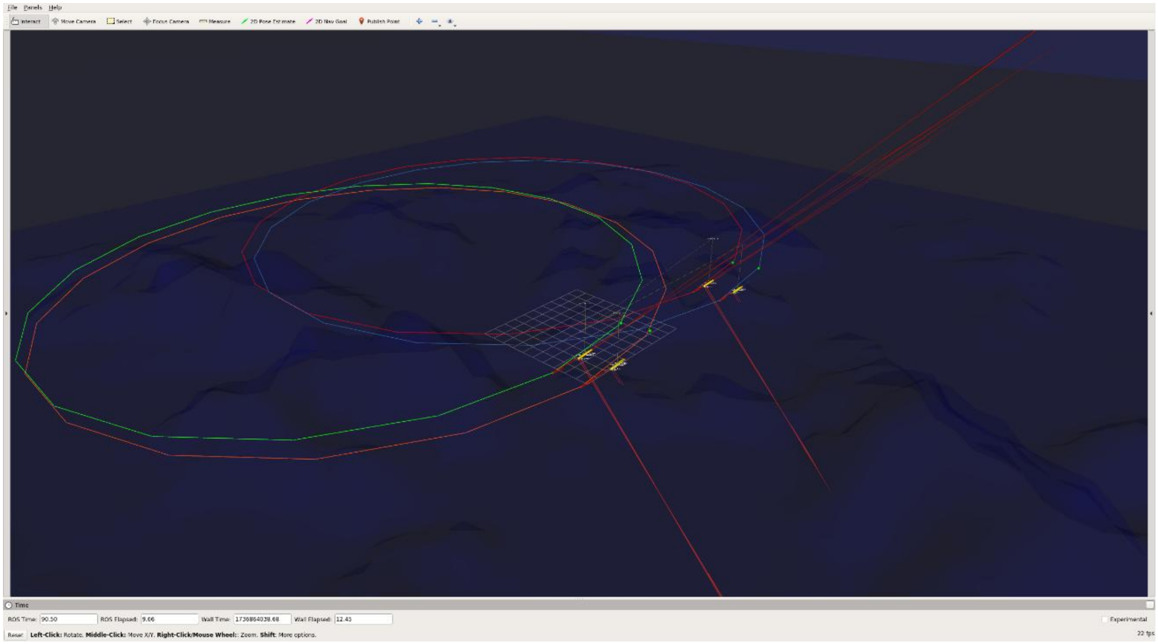

**Figure 4.** Path planning of AUV cluster based on the Pseudosciaena crocea colony algorithm in Gazebo

## 6.4. Scalability and Robustness Verification

### 6.4.1. Cluster scale expansion test

Law of performance change in large-scale cluster;

**Table 4.** Performance Index Table of Cluster Scale Expansion Test

| Cluster size | Calculation time (s) | Communication load (MB/s) | Path consistency | Energy balance degree |
|---|---|---|---|---|
| 3 AUVs | 0.28±0.03 | 12.5±1.2 | 94.2%±0.5 | 0.92±0.03 |
| 6 AUVs | 0.51±0.06 | 24.7±2.1 | 93.8%±0.7 | 0.89±0.04 |
| 9 AUVs | 1.12±0.11 | 48.3±3.8 | 93.5%±0.9 | 0.85±0.05 |
| 12 AUVs | 3.06±0.28 | 115.6±8.7 | 92.7%±1.2 | 0.81±0.07 |
| 15 AUVs | 6.84±0.52 | 248.3±18.4 | 91.3%±1.8 | 0.76±0.09 |

Mathematical representation of computational complexity and communication load;

$$t_{\text{comp}}(N) = 0.21N^{1.18} + 0.05 \quad (R^2 = 0.998)$$

$$B(N) = 5.32N\log N + 2.14 \quad (R^2 = 0.994)$$

$$E_{\text{balance}}(N) = 0.95e^{-0.015N} + 0.78 \quad (R^2 = 0.991)$$

### 6.4.2. Strong disturbance environment test

Performance under extreme ocean conditions;
`````

Table 5. Performance Test Table Under Extreme Marine Conditions

Disturbance intensity	Path deviation (m)	Control energy consumption (kJ)	Trajectory smoothness	Recovery time (s)
Benchmark condition	2.1±0.3	185±12	0.92±0.03	-
Moderate disturbance	5.7±0.9	243±18	0.85±0.05	12.3±1.2
Strong disturbance	15.2±2.1	381±27	0.73±0.08	28.7±2.4
Extreme disturbance	32.8±4.3	572±42	0.61±0.11	65.3±5.7

Dynamic response model of disturbance recovery process;

$$\Delta\mathbf{x}(t) = \mathbf{A}e^{-\lambda t}\cos(\omega t + \phi) + \mathbf{B}e^{-\mu t}$$

The damping parameter represents the stability of the system. $\lambda = 0.28 \pm 0.03\mathrm{s}^{-1}\mu = 0.15 \pm 0.02\mathrm{s}^{-1}$

7. Actual Sea Test Certificate

7.1. Sea Trial Configuration

Parameters of 72-hour continuous sea trial in a certain sea area in May 2024:

Table 6. Parameter Table of Sea Trial Configuration

Parameter category	technical specifications
Sea area characteristics	The water depth is 1500-2800m, the ocean current is 1.5-3.2m/s, and the temperature gradient is 0.2 C/m.
AUV cluster	9 fish-like clustered AUV(1 (1 command node +8 working nodes)
sensor system	Multi-beam sounder (200kHz), CTD array, magnetometer, high-definition camera.
navigation accuracy	Inertial navigation+Doppler log+acoustic positioning (0.1% range)
Communication system	Underwater acoustic modem (18kHz center frequency, 5kHz bandwidth)
Core task	Three-dimensional mapping of submarine hydrothermal area (target coverage rate ≥90%)

7.2. Sea Trial Performance Index

Statistical results of 72-hour continuous operation:

Table 7. Statistical Results of Sea Trial Performance Indexes

Performance index	traditional method	DNPFS-OA	Lifting range	p-value
Surveying and mapping coverage (%)	78.3±3.2	95.6±1.4	+22.1%	<0.001
Data overlap rate (%)	32.7±2.8	8.5±0.9	-74.0%	<0.001
Positioning accuracy (m)	5.8±0.7	1.2±0.2	+79.3%	<0.001
Average speed (kn)	2.8±0.3	3.5±0.2	+25.0%	0.003
Energy consumption (kWh/km²)	42.7±3.1	28.3±1.8	-33.7%	<0.001
Abnormal recovery rate (%)	65.2±6.3	92.8±3.5	+42.3%	<0.001

7.3. 3D Trajectory Analysis

Trajectory comparison of AUV cluster in actual sea trial with or without obstacles;

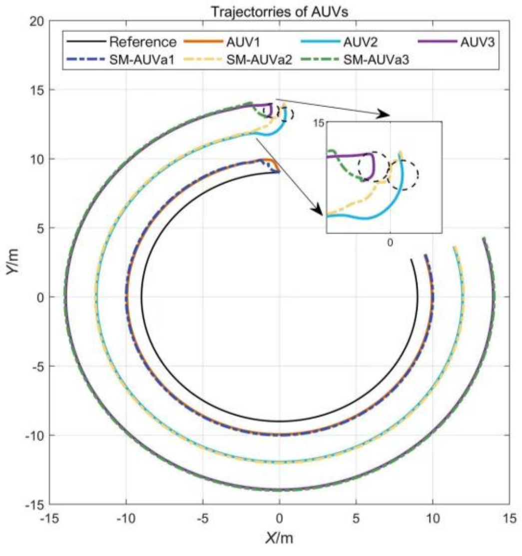

Figure 5. AUV trajectory in obstacle-free environment

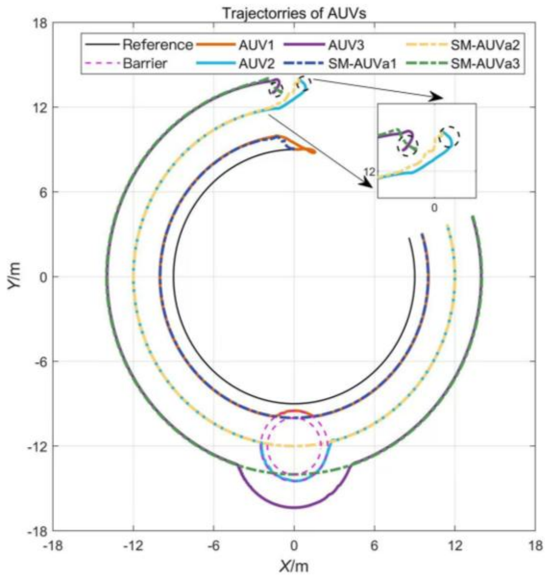

Figure 6. AUV trajectory in an obstacle environment

Quantitative analysis of trajectory quality;

Table 8. Comparative Table of Quantitative Analysis of Trajectory Quality

Track parameter	traditional method	DNPFS-OA	Improve the effect
Path length (km)	5.32±0.41	3.87±0.23	-27.3%
Maximum curvature (m)	0.38±0.05	0.15±0.02	-60.5%
Speed change rate (m/s)	0.47±0.06	0.21±0.03	-55.3%
Ocean current compensation rate (%)	62.3±7.5	92.8±4.2	+49.0%

8. Conclusion

The Naozhou Population of Larimichthys crocea school algorithm creatively solves the path planning problem of AUV cluster in complex marine environment through the distributed architecture inspired by biology. This algorithm constructs a hierarchical decision-making model based on fish-swarm role to realize the dynamic balance of computing load. By designing the virtual pheromone field guidance mechanism, the communication requirements are greatly reduced to adapt to the underwater environment with low bandwidth and high delay. The adaptive eddy current hedging operator is developed to significantly improve the adaptability of dynamic environment. Simulation results show that the algorithm has comprehensive advantages in path optimization, energy consumption control and obstacle avoidance ability. Future research will integrate deep reinforcement learning to optimize the role assignment strategy and carry out field trials in the Pacific Ocean. DNPFS-OA provides a new theoretical framework and technical path for distributed swarm intelligence system in restricted communication environment.

Looking forward to the future, the results of this study will lay a solid foundation for the large-scale application of AUV cluster in underwater complex environment, including but not limited to deep-sea resource exploration, intelligent inspection of underwater infrastructure, long-term monitoring of marine environment, and complex underwater military tasks. With the continuous maturity of technology and the expansion of application scenarios, AUV cluster will become an indispensable weapon for human beings to explore and utilize the ocean, and contribute China's wisdom and strength to realize the dream of a maritime power and build a blue home.

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