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Three-Dimensional Dynamics Simulation of Fish Schooling Integrating Physiological Characteristics, Movement Patterns, and Multi-Source Perception

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Abstract: During a long evolutionary process, fish schools in nature have developed complex self-organizing collective behaviors. These behaviors not only rely on local information exchange between individuals, but are also strictly limited by specific hydrological environments, individual physiological differences, and hydrodynamic effects. This article establishes a three-dimensional (3D) simulation of fish ecological dynamics, combining physiological metabolic constraints, composite perception, and heterogeneity characteristics. Based on classical local behavior interaction rules, a fluid dynamics based lateral line perception field and dynamic visual area calculation were introduced, and the process of energy recovery from wake vortices by clusters during swimming was quantified. Finally, three ecological scenarios were provided: biomimetic target induction, predator driven recombination, and hydrodynamic disturbance. This provides a reliable visual analysis tool for further exploring the ecological mechanisms of collective behavior in aquatic animals.

Keywords: Fish school simulation; Self-organizing behavior; Energy metabolism; Multi-source perception; Ecological response.

1. Introduction

The schooling, migration, and evasion behaviors of fish schools in natural aquatic systems have always been the main focus of ecological, behavioral, and biomimetic engineering research[1-3]. Hundreds to thousands of fish, without any central coordinating nodes, can complete collective behaviors such as formation maintenance, obstacle avoidance, and collective evasion by observing and perceiving the status of neighboring species.

Early research on simulating collective behavior mainly relied on three classic rules of local interaction: Separation, Alignment, and Cohesion. The relevant models provide a fundamental theoretical framework for simulating biological populations of different densities by dividing the space into exclusion, arrangement, and attraction regions [4-5]. However, early theoretical discussions often tended to view the entire school as a uniform particle system with uniform distribution and identical properties, ignoring the physiological heterogeneity commonly present in real biological communities and its impact on local information transmission gradients [6]. In actual fish swarm systems, there are objective physiological differences between individuals in terms of geometric shape, baseline swimming speed limitations, and sensitivity to seeking advantages and avoiding disadvantages. In addition, swimming in viscous fluid media does not involve maintaining a constant velocity. On the contrary, fish typically adopt intermittent swimming strategies, alternating between sudden acceleration and gliding [7]. The formation of this strategy is subject to endogenous limitations of aerobic metabolism rate and muscle fatigue, as well as the result of individuals adapting to complex hydrodynamic environments.

Previous fluid experiments have observed the presence of Karman vortex streets in the wake region, which allows following fish to reduce their swimming resistance by aligning with specific phase differences, thereby gaining energy advantages at the population level [8]. Due to the lack of potential physical environment fields and metabolic energy constraints in traditional phenomenological kinematic models, when simulating dense communities facing external predation pressure or strong interference from complex current environments, they often produce instantaneous turns and rigid formation maintenance, which violates physical knowledge and reduces the ecological credibility of simulation results [9]. In particular, compared with other groups, the visual barriers caused by underwater environment and their own physiological structure, as well as the dynamic blind spot effect caused by spatial local fluid repulsion of fish's lateral line system, cannot be ignored [10]. This is rarely discussed in current fish swarm simulation systems.

Based on the above research background and the limitations of existing models, this paper proposes an improved three-dimensional ecological dynamics simulation method for fish schools at the time continuous dynamic scale.

This method consists of three components: independent metabolic state automata for each entity, fine quantification of visual impairment effects, and simulation of local fluid dynamics interactions in lateral line sensing.

In addition, the framework aims to adapt to various ecological disturbances. By systematically collecting and continuously analyzing emerging statistical descriptors such as aggregation, polarization, and milling, this tool can quantitatively investigate collective behavior.

2. Individual Physiological Heterogeneity and Intermittent Metabolic Mechanisms

The basis for maintaining the macroscopic evolution of fish community structure is the evolution of the microscopic state of the underlying individuals. Therefore, individual fish in three-dimensional space can be viewed as entities with independent physiological parameters and action decision cycles. Their basic motion states are described and iterated through continuous position and velocity vectors. Due to objective differences in body size and swimming ability among natural fish individuals, physiological heterogeneity factors need to be considered. Therefore, in the initialization stage of the simulation, we assign health coefficients and bold feature coefficients to each individual according to a normal distribution [11]. This enables the group to spontaneously appear in a natural configuration centered around superior individuals during the movement process. In the model program, initialize the physiological differences of individuals using Gaussian distribution functions:

```
    this.perfTrait = Math.max(0.5, randomGaussian(1.0, 0.2));
    this.boldness = Math.max(0.5, randomGaussian(1.0, 0.2));
    this.maxSpeed = PARAMS.maxSpeedBase * this.perfTrait;
    this.maxForce = PARAMS.maxForceBase * this.perfTrait;
    this.separationRadius = PARAMS.lateralLineDist /
this.boldness;
```

Specifically, an individual's maximum swimming speed and maximum output thrust are strictly limited by their physical health characteristics, while the safe distance for collision avoidance is determined by their bold coefficient in reverse. In order to more accurately reflect the fish swarm, individual motion is further modeled as a discrete state switching process alternating between sudden acceleration and unpowered sliding. For individuals in an explosive state, their energy consumption rate is manifested as a non-linear combination of the square of the ratio to their current swimming speed. This setting simulates the accumulation process of lactate when fish flap their tails [12]. In program implementation, the dynamic metabolic cost is calculated as follows:

```
    let speedRatio = this.velocity.lengthSq() / (this.maxSpeed *
this.maxSpeed);
    let dynamicCost = PARAMS.burstCost * (0.2 + 0.8 *
speedRatio);
    this.energy -= dynamicCost;
```

In the stage of unpowered sliding, the individual's speed decays exponentially under the resistance of viscous fluid. A correction algorithm based on dynamic oxygen debt calculation and wake energy recovery is proposed to address the lack of evaluation of energy loss and fluid dynamics gain during continuous distance swimming of fish. This algorithm enables individuals to continuously adjust their power output between energy consumption and replenishment thresholds, effectively avoiding the distortion of traditional constant velocity derivation models and allowing the population to macroscopically exhibit a propulsion pattern characterized by periodic bursts with physiological limitations [13-14].

In addition, in order to maintain the sustainable operation of the system and avoid stagnation caused by energy consumption, this article introduces a food renewal mechanism to simulate the way fish obtain energy in real life. In order to maintain vital signs, when hunger levels exceed a threshold, chemotactic traction dominates the resulting acceleration. In the energy rich gliding cycle without explicit external induction, individuals will perform relevant random walks with inertia preservation to explore food signals with attenuation characteristics in the environment.

3. Multi-Source Environmental Perception and Hydrodynamic Interaction Mechanisms

After completing the individual modeling, we further consider replicating the interactions between individuals. The navigation and formation maintenance of fish schools in complex underwater environments highly depend on the multi-channel information fusion of the visual and lateral line systems. In addition to traditional distance threshold judgments, the model introduces dynamic perception geometric fields and fluid interaction forces correlated with velocity vectors.

Vision serves as the primary mechanism by which fish schools acquire social information across moderate to extended spatial ranges. An individual's effective visual range depends not only on the basic physiological radius limit but is also set as a negatively correlated function of its velocity vector [15]. During burst swimming events, the individual's visual cone angle contracts, creating a tunnel vision effect that dynamically filters out secondary interaction nodes to the rear and sides [16]. This explains the phenomenon in which the local following mechanism temporarily fails when real fish schools scatter and escape in response to a sudden scare. The calculation of the dynamic blind spot is implemented in the program through linear interpolation:

```
    let speedRatio = Math.sqrt(fish.velocity.lengthSq()) /
fish.maxSpeed;
    let dynBlindSpot =
THREE.MathUtils.lerp(PARAMS.blindSpotDot, 0.2,
speedRatio);
```

For near end spatial perception, this model establishes a physical repulsive field by simulating a lateral line system. In order to solve the distortion problem of unrealistic repulsive field caused by absolute boundary judgment, this simulator utilizes a smooth and softened repulsive potential field function based on relative velocity projection. When the distance between adjacent individuals is less than the safety threshold and the relative velocity projection is positive, the force field will generate a geometric series that avoids acceleration. This goes beyond traditional visual following priorities, ensuring that the community does not experience rigid geometric overlap while maintaining a dense gathering state [17].

In addition, at the level of fluid dynamics interactions, the system quantifis the Kármán vortex street effect. When an individual creates a specific length of conical slipstream during explosive swimming, the same species of animals moving in the same direction within that area will experience hydrodynamic traction. Therefore, they can maintain swimming speed and achieve partial energy recovery with lower active thrust [18]. This program determines the influence range of wake based on the relative position and velocity direction vector between individuals:

```
    if (forwardDot < -0.7 &&
fish.velocity.dot(other.velocity) > 0) {
        let parallelLen = forwardDot * dist;
```

```
    let centerLinePos = other.position.clone().add(otherDir.clone().multiplyScalar(parallelLen));
    let lateralOffset = fish.position.clone().sub(centerLinePos).length();
    if (lateralOffset < 1.0) {
        let pullForce = PARAMS.wakeStrength * (1.0 - dist / PARAMS.wakeLength) * fish.maxForce;
        fish.energy = Math.min(1.0, fish.energy + 0.002);
    }
}
```

If an individual is in the turbulent boundary layer at the edge of the wake, they are subjected to a lateral shear disturbance torque. This asymmetric reward and punishment mechanism based on the flow field position prompts the fish school to spontaneously seek optimal stagnation points in a hydrodynamic sense, evolving into an interlocking formation structure.

4. Group Behavioral Decision-Making and Environmental Boundary Response

After synthesizing local environmental perception information, individuals must use a corresponding weighted decision making logic to synthesize the final motion vector to cope with peer interaction demands and physical constraints of the external spatial environment. The model introduces an adaptive weight network based on physiological trait gradients when calculating group alignment and cohesion expectations [19]. An individual's trust weight towards valid neighbors is jointly regulated by the cube of the spatial distance and the ratio of their physical fitness traits.

Individuals with robust physiques possess a higher influence weight in interactions; their action deflections can more effectively pull surrounding neighbors[20]. All resulting expected vectors are subtracted from the individual's current velocity and smoothed through a limiter to suppress system oscillation at high speeds. In the calculation of distance weighting and heterogeneous attribute fusion, the program segment normalizes it through the following logic:

```
let sizeRatio = other.perfTrait / fish.perfTrait;
let domWeight = (1.0 / (dist + 1.0)) * Math.pow(sizeRatio, 2.0);
totalSocialWeight += domWeight;
align.add(other.velocity.clone().normalize().multiplyScalar(domWeight));
```

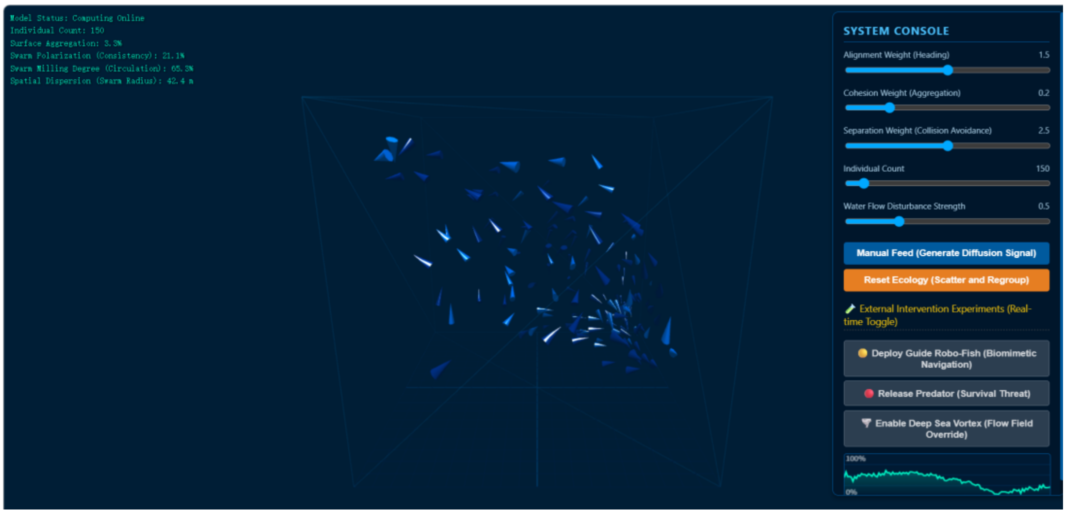
Subsequently, for better observational effects, we restrict the fish school's activities to an enclosed simulation space. The 3D enclosed simulation space simultaneously introduces a proactive boundary predictive control based on the normal component of velocity. When an individual approaches the simulation boundary and its velocity points outwards, the system calculates an urgency coefficient based on the penetration depth and normal velocity, thereby generating a normal penalty thrust to force it to decelerate and turn tangentially. This flexible avoidance strategy effectively absorbs the system inertial energy brought about by high speed movement, guarantees the relative integrity and continuous fluidity of the internal configuration when the fish school swims in restricted waters, and simulates the reaction of real fish schools[21].

5. Ecological Intervention Scenario Simulation

External environmental mutations and changes in artificial ecological intervention conditions are important means of testing community behavioral response mechanisms and system robustness. This paper designs three typical intervention variables. First, in the flexible accompanying control experiment with a biomimetic pilot target, the system introduces a robotic fish [22] entity cruising along a preset low frequency periodic trajectory into the simulated waters, facilitating observation of the guiding effectiveness of specific signal sources on the biological community. Second, a predator is introduced to observe the evasion behavior of the fish school towards predators[23]. Furthermore, a nonlinear vortex flow field containing normal contraction and tangential rotation vectors is introduced. Individuals with lower baseline speeds are unable to resist the fluid drag and deviate, but core individuals with higher physical fitness traits in the group actively increase metabolic output to resist the fluid traction[24].

6. Operation Guide for the 3D Ecological Dynamics Simulator

Here we introduce the main interfaces and functions of the simulator, along with demonstrations of the corresponding effects.



```
Model Status: Computing Online
Individual Count: 150
Surface Aggregation: 3.3%
Swarm Polarization (Consistency): 21.1%
Swarm Milling Degree (Circulation): 65.3%
Spatial Dispersion (Swarm Radius): 42.4 m
```

SYSTEM CONSOLE

Alignment Weight (Heading) 1.5

Cohesion Weight (Aggregation) 0.2

Separation Weight (Collision Avoidance) 2.5

Individual Count 150

Water Flow Disturbance Strength 0.5

Figure 1. Simulation Interface

Figure 1 shows the simulation interface, equipped with a complete dynamic control panel. The top right corner of the simulator interface provides a real time parameter adjustment system containing sliders and trigger buttons. This allows users to smoothly alter global physical variables during the continuous integration evolution process and observe the transient response characteristics of the biological network topology.

The first section of the control panel is the core interaction weight control area, mainly containing three continuous adjustment sliders: separation weight , alignment weight, and cohesion weight. The alignment weight sets the individual's physical tendency to align with the average velocity vector of its neighborhood. Moderately increasing this parameter encourages the school to present a highly consistent cruising posture, but they are prone to overall yaw lag caused by excessive coupling when facing obstacles. The cohesion weight controls the gravitational constant for individuals gathering towards the local center of mass. Setting it in a lower range helps maintain the degrees of freedom within the community. If the value is too high, it will cause the group to collapse infinitely towards the center, thereby triggering the underlying anti-penetration penalty force field. The separation weight defines the sensitivity gradient of the lateral line system to collision threats and is a key parameter for maintaining the spatial dispersion of the population.

The second section of the control panel involves environmental settings and ecological event triggers. The individual count slider allows users to dynamically add or delete swimming entities during the system's operational cycle; the system automatically handles the coordinate distribution of new individuals and memory reclamation for removed ones. The current disturbance strength slider controls the sine wave amplitude of the global background flow field to simulate natural turbulence in different water environments. The ecological event area below the console provides various discrete interaction functions. These include a manual feed button to generate a food gravitational field signal with a decay period, and an ecological reset button to clear existing physical fields and respawn the population coordinates according to the initial Gaussian distribution.

In the external intervention experiment module, users can inject advanced ecological variables via three state toggle buttons. The "Deploy Guide Robo-Fish" button generates an independent moving entity at the center of the space that emits a mandatory following gravity, allowing observation of its indirect induction process on large scale clusters. The "Release Predator" button instantiates an entity with high maneuverability and hunting tendencies, used to test and record network rupture and stress evacuation data when the community suffers physical penetration. The "Enable Deep Sea Vortex" button directly overwrites the global background flow field, generating a centripetally rotating nonlinear hydrodynamic constraint at the origin. In addition, the bottom of the interface is equipped with a real time refreshing polarization line chart and statistical data window, which quantitatively feeds back the current proportion of surface aggregation of swimming individuals, group movement consistency, angular momentum around the core, and spatial average dispersion, providing intuitive data support for macroscopic behavioral analysis.

The following shows some simulation effects. Figure 2 shows spontaneously formed group behavior, Figure 3 shows tracking of the robotic fish, Figure 4 shows evasion of a predator, and Figure 5 shows the reaction to an introduced flow field.

Figure 2. Spontaneously formed group behavior

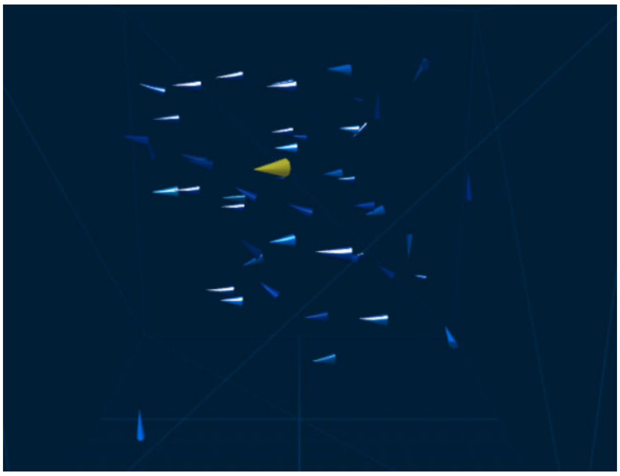


Figure 3. Tracking of the robotic fish

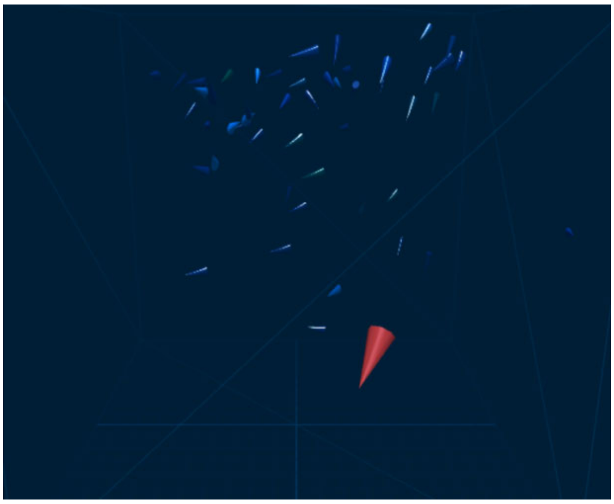


Figure 4. Evasion of a predator

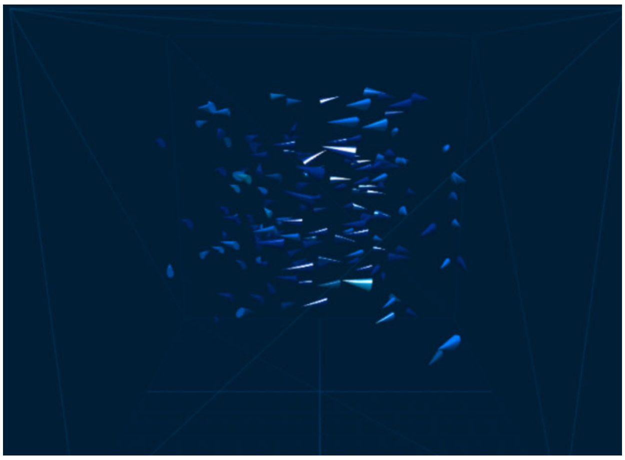


Figure 5. Reaction to an introduced flow field

7. Conclusion

Based on the ethological evolution laws of fish school behavior in complex 3D water environments, this paper proposes and implements an ecological dynamics simulation framework that integrates individual physiological state constraints with a hydrodynamic foundation. By introducing a physiological parameter based on probability distribution and a nonlinear metabolic energy pool model, the system effectively replicates the intermittent swimming phenomenon of fish that accords with natural observation rhythms. Regarding optimizations at the perception level, the calculation of the dynamic visual blind spot, the improved flexible lateral line repulsion force field, and the traction coupling mechanism of the Kármán vortex street wake jointly enhance the physical coherence of simulated individuals in microscopic interactions and environmental evasion. The external methods set up, such as biomimetic target induction, predator threats, and nonlinear complex flow field interference, also provide conditions for further research on the drivers of group behavior. The data and modeling concepts provided by this simulation study help deepen the understanding of the ecological mechanisms of collective motion in high density aquatic organisms in nature, while also providing a theoretical basis for algorithm optimization and motion decision design in related underwater swarm bionic engineering.

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