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Motion Control and Motion Coordination of Bionic Robotic Fish: A Review

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Abstract

Fish's outstanding motion and coordination performance make it an excellent source of inspiration for scientists and engineers aiming to design and control next-generation autonomous underwater vehicles within the framework of bionics. This paper offers a general review of the current status of bionic robotic fish, with particular emphasis on the hydrodynamic modeling and testing, kinematic modeling and control, learning and optimization, as well as motion coordination control. Among these aspects, representative studies based on ideas and concepts inspired from fish motion and coordination are discussed. At last, the major challenges and the future research directions are addressed in the context of integration of various research streams from ichthyologic, hydrodynamic, mechanical, electronic, control, and artificial intelligence. Further development of bionic robotic fish can be utilized to execute some specific missions in complex underwater environments, where operations are unsafe or impractical for divers or conventional underwater vehicles.

Keywords: bionic robotic fish, motion control, coordination control, fish swimming, learning and optimization

1 Introduction

As the result of million years of selection and evolution in aquatic world, fish can perform fast, efficient, and agile swimming motions. With more than 28,000 species, fish are endowed with a variety of appealing morphological and structural features for moving through water with prominent efficiency, speed, maneuverability, and stealth, which substantially exceed current man-made underwater vehicles[1–6]. More remarkably, fish are able to perform high-speed and high-maneuverability swimming while leaving little traceable wake structure. Within the framework of bionics, a bioinspired approach is utilized to transfer biological features and locomotion abilities of fish to design and control Autonomous Underwater Vehicles (AUVs). Thus, a bionic robotic fish can be defined as a fish-inspired propulsion system relying on undulatory or oscillatory motions to move through the water. Bionic robotic fish is the integration of ichthyologic, hydrodynamic, mechanical, electronic, control, and computer disciplines, offering a controllable and scalable robotic platform for biological research (*e.g.*, testing hypotheses in biology) and a prototype technology for engineering practice. As a consequence, bionic robotic fish have witnessed a multitude of applications such as oceanography, underwater exploration, archaeology, search and rescue, patrol, marine environmental monitoring, ocean sampling, and mobile sensing, where operations are unsafe or impractical for divers or conventional underwater vehicles[7–15].

In reality, the bionic works emphasize alikeness not only in external appearance but also in internal mechanism. Similarly, efforts to build bionic robotic fish focus on many aspects varying from bionic morphology, sensing, neural control, to function, which primarily include kinematic and hydrodynamic analysis, mechanical design, control methods, and aquatic tests[16]. The first endeavor to develop freely swimming robotic fish can be traced back to the early 1990s, accompanied by the RoboTuna and RoboPike projects at MIT and Draper Laboratory[17–19]. Since then, there has been an ever-growing interest in creating various robotic prototypes[16,20,21], such as 3D swimming robotic fish[22–24], boxfish-like robot[25,26], robotic manta ray[27], robotic mackerel[28], two-caudal-fin robotic fish[29], amphibious robotic fish[30,31], wire-driven robotic fish[32], and soft robotic fish[15], as shown in Fig. 1. Although different

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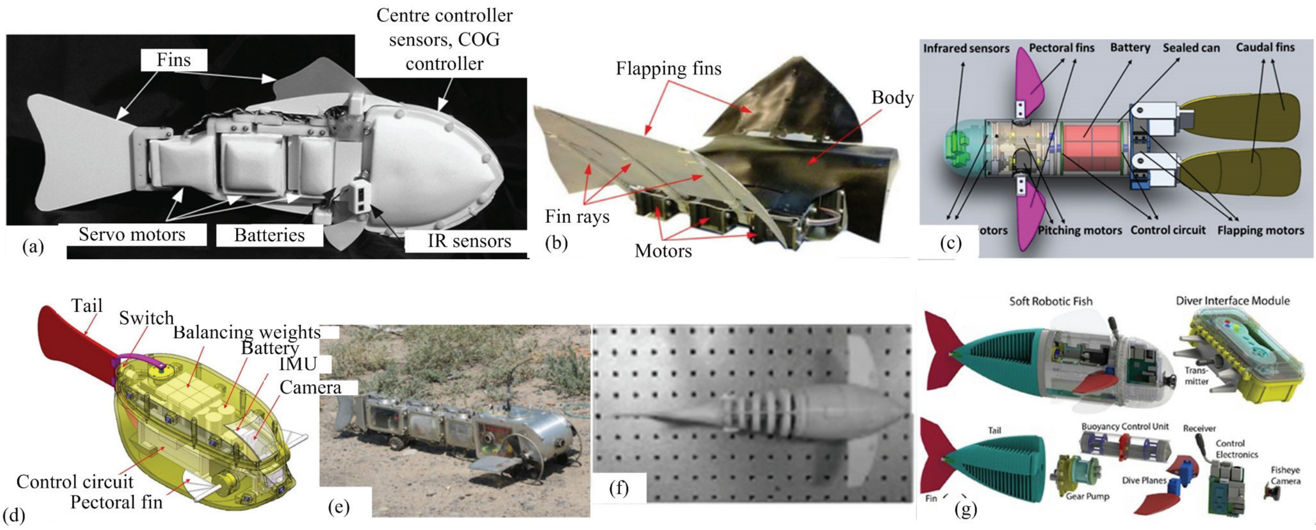

Fig. 1 Various robotic fish prototypes. (a) G9 robotic fish[24]; (b) robotic manta ray[27]; (c) two-caudal-fin robotic fish[29]; (d) boxfish-like robot[26]; (e) amphibious robotic fish[30]; (f) wire-driven robotic fish[32]; (g) soft robotic fish[15].

propulsion modes exhibit, most of them fall into two categories in terms of the body part utilized for propulsion: Body and/or Caudal Fin (BCF) propulsion, and Median and/or Paired Fin (MPF) propulsion[33]. The latter may be subdivided into pectoral fin propulsion and undulation fin propulsion. Real fish do not exclusive depending on one locomotor mode, but combine multiple locomotor behaviors allowing them to better adapt to their dangerous aquatic environments. Like adaptation in avian flight, swimming behaviors in fish may be regarded as a compromise between stability and maneuverability. Specifically, BCF propulsion is intrinsically stable and is well suited for long-term swimming at relatively high speeds, while MPF propulsion has the advantage of maneuverability and is often seen in smaller fish that need elegant escape patterns[33,34]. Accordingly, it is difficult to determine which swimming pattern is optimal since different living conditions and habitats exist. Indeed, fish have the ability to plastically respond to a myriad of environmental changes[35]. Similar to real fish, the robotic fish adopting different propulsive modes can perform different propulsive capabilities. Specially, robotic fish in BCF locomotion always obtain relatively high swimming speed and these in MPF locomotion can reach great maneuverability. Certainly, different BCF robotic fish own different capabilities. For example, the robotic fish inspired by anguilliform swimmers like eels often have multiple Degrees of Freedom (DoFs) whose whole body takes part in undulation. As a result, these robots generally obtain high maneuverability, low speed as well as low hydrodynamic efficiency. By contrast, the robotic fish inspired by tunas always employ the peduncle and caudal fin for oscillation and can obtain very high propulsive speed as well as efficiency, but their maneuverability is relatively low, like a larger turning radius than anguilliform robots. As for the MPF robot, they always have little turning radius and stable navigation attitudes, but low propulsive speed.

Besides adaptation to changing environments by adjusting swimming patterns, fish may utilize coordination behaviors to achieve useful tasks such as avoiding predators, capturing prey, and breeding offspring[36]. In contrast to a single robotic fish's motion control, motion coordination pays much more attention to cooperative behaviors among multiple robotic fish, even a robotic fish group. As demonstrated in BBC's Blue Planet II, some fish like sardines and snapper swim together in tight-knit groups. Such a schooling behavior is beneficial in reducing drag and escaping from enemies. Considering that the capability of a single robotic fish may be limited due to the uncertainty and parallelism of the missions, creating an artificial multi-fish system that replicates coordination mechanism of fish flock is a favorable solution. Moreover, coordination control of multi-agent systems has been an active research subject extensively investigated by the systems and control theory community. Particularly, rapid improvements in robotics, Artificial Intelligence (AI), and machine learning have contributed to the swift uptake of the learning and optimization technology in motion control of a wide array of robots. Meanwhile, swarm intelligence-based techniques are increasingly applied to different fields such as robotics, data mining, medicine, and blockchains. Theoretical and empirical research in collective biological systems like a school of fish, a flock of birds, or a swarm of insects is an essential step towards intelligent control of unmanned air, ground, and maritime vehicles. Simply put, fish-inspired Artificial Fish School Algorithm (AFSA)[37] and coordinated control techniques considerably promote the development of motion control and optimization of unmanned vehicles.

The purpose of this paper is twofold. The first is to offer a structured review of an amount of literatures that is interwoven with biology and robotics using a motion control framework. The second purpose is to analyze the existing studies to identify commonalities, thereby providing innovative and inspirational guide for development and deployment of bionic AUVs under the background of fast-moving AI. Emphasis is then given to such topics as dynamic modeling and control, kinematic modeling and control, learning and optimization, as well as coordination control. Many previous review papers have been reported the development of the robotic fish in the last two decades[38-41]. For example, Bandyopadhyay *et al.* surveyed the roles of pectoral appendages in maneuvering motions of aquatic animals[38]; Liu *et al.* reviewed classification of propulsive modes, corresponding characteristics, international research situation, and future research issues of the biomimetic robot fish[39]; Raj and Thakur reported a detailed comparison of various design features like sensing, actuation, autonomy, waterproofing, and morphological structure of different types of fish-inspired robots[40]; Scaradozzi *et al.* surveyed the state of the art on biomimetic robotic fishes, and discussed the reasons why bio-inspiration can be a winning move as well as how fish swimming can be the line of sight of the future locomotion technology[41]. As opposed to these previous review papers, this paper mainly covers modeling and control aspects, as well as the combination of control algorithms and AI with relevance to technological applications. Accordingly, only representative literature with relevance to motion control analysis and design is discussed. We hope that this paper will shed light on the iterative interaction of fish biology and engineering technology, contributing to updated design and control of innovative underwater vehicles.

The remainder of this paper is organized as follows. We start by offering an overview of the hydrodynamic modeling and testing of fish swimming in section **2**. The kinematic modeling and control aspects of bionic robotic fish are provided in section **3**. The learning control and motion optimization issues as well as coordination control methods are detailed in sections **4** and **5**. Some critical issues and future developments of the bionic robotic fish in the context of advanced motion control are summarized in section **6**.

2 Hydrodynamic modeling and testing

As schematically illustrated in Fig. 2, modeling and control are two critical issues in developing and utilizing bionic robotic fish. In many robotic fish-based applications, it is also essential to have a deep understanding of hydrodynamic and kinematic principles of fish swimming. The hydrodynamic and kinematic models not only provide a tool to quantify key physical processes acting between swimming organism and surrounding fluid, but also guide the engineering design and the assessment of extrinsic effects. This section briefly introduces hydrodynamic modeling and testing methods in fish swimming.

2.1 Hydrodynamic modeling

Most of fish achieve propulsion by using wavelike movements of the fish's body and tail, while other specialized fish do by using movements of the fins. Whichever propulsive pattern is used, fish locomotion is characterized by deforming bodies, fluid forces, and their interactions. Owing to the complexity of hydrodynamics and kinematics of swimming organisms, it is difficult to establish an accurate hydrodynamic model allowing motion control and performance analysis of bionic robotic fish. That is, the most complicated and challenging issue of dynamic modeling lies in capturing the hydrodynamics of fish swimming[34,43,44].

Existing methods for hydrodynamic modeling can be classified into two categories: numerical methods and

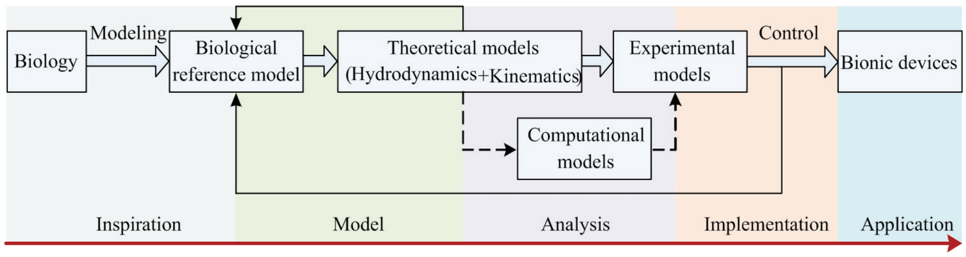

Fig. 2 Schematic process flow to produce bionic devices. (Adapted from Ref. [42].)

analytical methods. Specifically, numerical methods often require solving the Navier-Stokes equations, which are accurate but extremely time-consuming. Meanwhile, hydrodynamic interaction of the flexible body and fins for natural fish can be modeled by using the linear Euler-Bernoulli beam model[45,46]. By contrast, analytical modeling methods are more feasible and practical for robotics. The first analytical model of fish swimming is the resistive force theory[47]. In this model, the fluid forces are composed of longitudinal skin friction and lateral drag forces. But the resistive force theory does not take inertia forces into consideration. The waving plate theory[48] analyzes the hydrodynamics by modeling fish as an undulating infinite height plate. In comparison with the waving plate theory, Lighthill's theory[49–51] are more pertinent for modeling of swimming robots, including the Elongated Body Theory (EBT) and the Large Amplitude Elongated Body Theory (LAEBT). The EBT captures the added mass effect, and approximates the effect of wake dynamics based on the kinetic momenta balance in a hemisphere control volume containing the fish body. The LAEBT extends the EBT to the cases of large amplitude body deformations. Because of the good balance between fidelity and simplicity, Lighthill's theory has been widely utilized in hydrodynamic modeling of robotic fish[43,52,53]. Additionally, the quasi-steady lift and drag models from the airfoil theory are also commonly used hydrodynamic modeling methods for bodies or fin surfaces of robotic fish[54,55]. The details are listed in Table 1.

Hydrodynamic parameters are crucial for an accurate dynamic model of robotic fish. Undoubtedly, how to obtain the hydrodynamic parameters is an inevitable problem in hydrodynamic modeling. In general, four types of approaches have been utilized in previous literatures: estimating by existing standard cases[43,56], calculating by Computational Fluid Dynamics (CFD) simulations[55], performing experimental measurements[46,53,57], and identifying from motion data[54]. In the first method, the parameters are estimated through approximating a robotic fish by standard shapes whose hydrodynamic parameters are already available under certain fluid conditions. But it is not appropriate to robots with irregular and complex geometric profiles, since no references can help to determinate the parameters. The CFD method requires the shape model of a robotic fish and outputs a theoretical result, which is not necessary in accord with the actual situation. Regarding the method of experimental measurements, particular measuring instruments are required, and the measurements are basically restricted to drag and thrust coefficients. In contrast, it may be practical and convenience to identify parameters directly from motion data, which can be captured simply by video cameras or onboard sensors with the robotic fish swimming freely. Indeed, identification approaches have been widely studied for ships[58,59] and underwater vehicles[60,61]. Using a combination of the parameter identification technique and modeling approach, Yu *et al.* proposed a data-driven dynamic modeling method for multi-joint robotic fish with irregular geometric profiles and numerous heterogeneous hydrodynamic parameters[62].

2.2 Hydrodynamic experimental techniques

Besides theoretical calculation of the fluid forces on a swimming fish, experimental techniques have been developed to quantitatively visualize and analyze the generated wake. Early work on fish swimming hydrodynamics mainly used qualitative shadowgraphy techniques[63]. Later, noninvasive techniques such as Particle Image Velocimetry (PIV) were increasingly used to quantify wake hydrodynamics behind swimming fish. A standard PIV apparatus comprises a single CCD or CMOS camera, a strobe or laser with an optical

Table 1 Comparison of analytical modeling methods for fishlike swimming

Theories	Characteristics	Application scenarios
Resistive Force Theory (RFT)	• viscosity plays the leading role in the fluid • the force between a small section of fish and the water was regarded as a resistive force depending exclusively on the instantaneous value of the velocity • not considering the inertia forces	• low Reynolds number • microscopic organisms swimming in viscous fluid • long narrow animals
Waving Plate Theory (WPT)	• the fluid is incompressible and inviscid, but with the Kutta condition imposed at the trailing edge of the plate • a two-dimensional flexible and thin plate performs the motion consisting of a progressing wave of given wave length and phase velocity along the chord • the basic mechanism of swimming is elucidated through applying the principle of action and reaction	• large Reynolds number • a two-dimensional flat fish and the aeroelasticity of oscillating wings
Elongated Body Theory (EBT)	• propulsive thrust is from reactive forces between the surface of the body and the volume of surrounding water • the cross-sectional area of the body is much smaller in the swimming direction than in the nearly perpendicular direction of the undulatory motion	• large Reynolds number • slender fish with a caudal fin in which each individual bony ray makes only a moderately small angle with the backbone
Large Amplitude Elongated Body Theory (LAEBT)	• extends the EBT to the cases of large amplitude body deformations • the large fish flexures and lateral velocities applied in propulsion is considered • the recoil is particularly estimated	• large Reynolds number • the fish with a relatively large amplitudes of tail motion

arrangement to limit the physical region illuminated, a synchronizer to act as an external trigger for control of the camera and laser, the seeding particles, and the fluid under investigation. Meanwhile, PIV software is exploited to process the acquired optical images. Note that the cross-correlation between parts of the two images where pattern generated by particles can be seen is used for the computation of the velocity field. Now there are several extensions of classic PIV setup, including tomographic PIV, stereo PIV, defocusing digital PIV, and so on. For instance, Fig. 3 presents a typical stereo PIV measurement system and the measured velocity vectors behind a turning fish[64]. The prominent merit of the PIV technique is its ability to non-intrusively measure high-resolution 2D or 3D velocity fields[65].

From the existing studies on measurement of velocity fields around a fish, there are three basic categories according to the used experimental setup[66]. In the first category, the fish is not within the field of view of the camera. The second category is the one in which the fish swims against the incoming flow and its body position keeps stationary in the field of view of the camera. In the third category, the fish performs free-swimming within the test tank. For instance, Müller *et al.* used 2D PIV to visualize the flow around the aquatic animals and to demonstrate the creation of vorticity and their contribution to thrust generation[67]. Drucker and Lauder explored the bluegill sunfish pectoral fins 3D wake structures using PIV[68]. Sakakibara *et al.* utilized stereoscopic PIV for capturing three components of velocity distribution on live goldfish along with particle tracking velocity in order to determine spatial velocity, acceleration, and vorticity[64]. In essence, fish locomotion can be regarded as a 3D swimming behavior, with multifarious fin and body motions and fin–wake interactions. With great progress made in laser technologies and electronic imaging systems, quantitative wake analysis of 3D locomotion of a freely swimming fish comes into reality. As an illustrative example, Mendelson and Techet applied synthetic aperture PIV to quantitatively analyze the wake behind a free-swimming giant danio in steady swimming and maneuvering, offering fast and accurate reconstruction of 3D particle and velocity fields[65]. In addition, a growing number of robotic models are applied to hydrodynamic experiments on aquatic animal propulsion. In the meantime, experimental self-propelled swimming methods (see Fig. 4) have demonstrated the potential for better replication of biological characteristics in biofluid and biomimic studies[69,70].

3 Kinematic modeling and control

In classical mechanics, kinematics refers to the study of properties of motion, typically involving position, velocity, and acceleration. To capture the motion essence of fishlike propulsion and maneuvering,

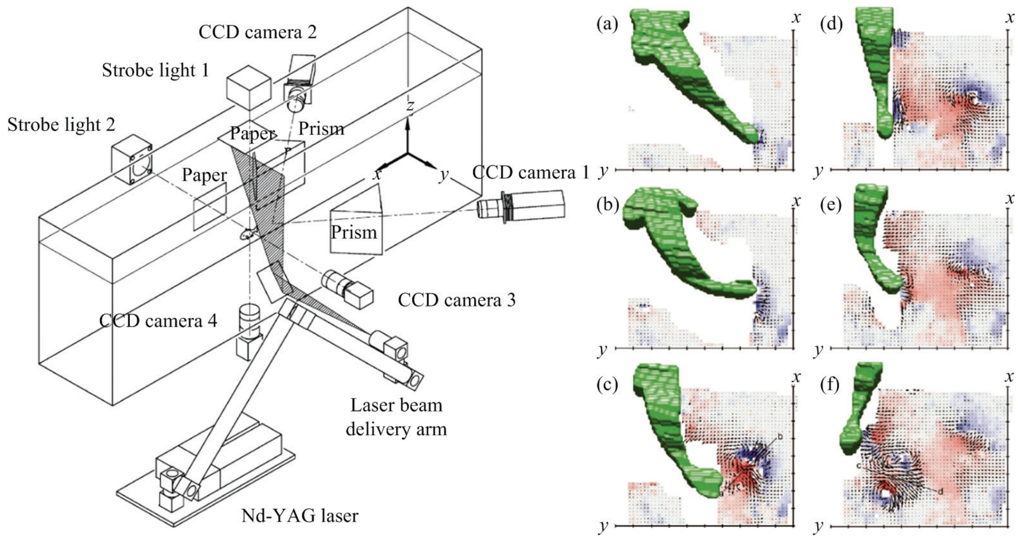

Fig. 3 Stereo PIV measurement system and velocity vectors behind a turning fish. (Adapted from Ref. [64].)

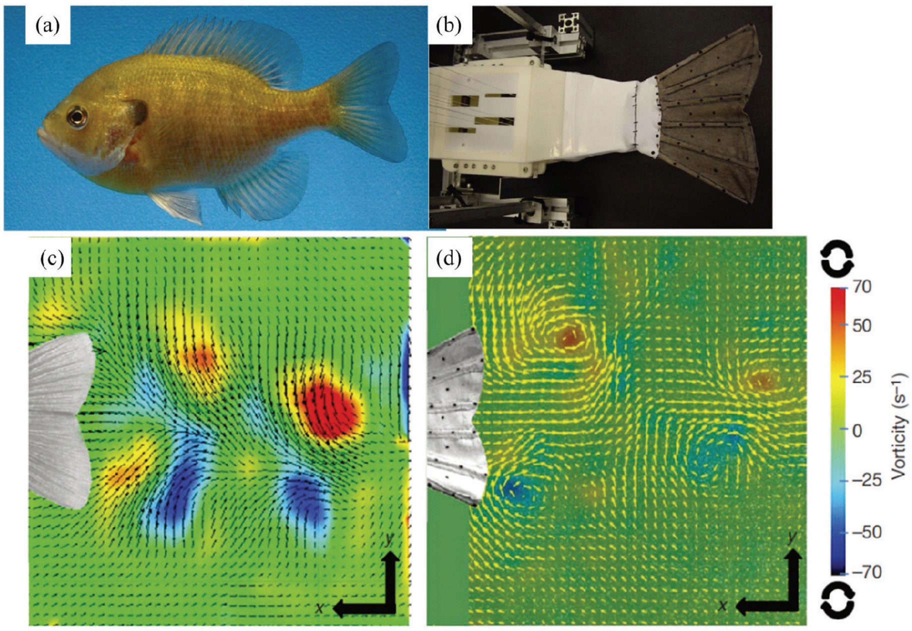

Fig. 4 DPIV images from a lateral view of a bluegill sunfish and the robotic caudal fin during rolling tail motion. (a) A bluegill sunfish; (b) a robotic caudal fin; (c) DPIV images of the bluegill sunfish; (d) DPIV images of the robotic caudal fin. (Adapted from Ref. [70].)

quantification of swimming kinematics is required in real 3D space. The acquisition of fish swimming kinematics further provides guidance for the formation of motion control methods.

3.1 Kinematic measurement of fish swimming

Kinematic measurement and analysis often require fish to perform spontaneous and continuous swimming behaviors so as to obtain the subject's spatiotemporal location as precisely as possible. Two fundamentally different approaches are usually employed to reflect the actual kinematic characteristics[71]. One is to record voluntary movements of fish swimming in still water, while the other is to induce fish to swim against the water flow at different speeds. The early manual quantification of fish kinematics suffers from systematic errors. Later, using the video-tracking approach to kinematic measurement of fish swimming has gained prominence in the field of biomechanics. It can be further categorized into 2D and 3D in terms of the position of fish. For example, Wu *et al.* presented a video tracking system which was able to measure 3D kinematics of a free-swimming fish[72]; Wang *et al.* performed a 3D kinematic analysis of a Koi Carp pectoral fin by simultaneously analyzing two views of the fins in the context of digital images processing[73]; Voesenek *et al.* proposed a validated method to track a fish in 3D by reconstructing its position, orientation, and body curvature from multi-camera high-speed video[74]; Audira *et al.* developed a single-camera-based tracking system for capturing 3D swimming behavior of multiple zebrafish with low cost and precise spatial position[75]. By means of 2D tracking system containing an *X*-*Y* translation stage and two cameras, Wu *et al.* achieved simultaneous measurement of kinematics and flow in the wake of a freely swimming fish[71]. Remarkably, Qian and Chen proposed a tracking system that was based on top-view tracking and supplemented by side-view tracking, allowing simultaneous 3D motion tracking of multiple fish[76]. Such advancements hold great potential for in-depth fish behavioral research.

3.2 Motion control

Motion control of robotic fish is another important research topic. In order to mimic control mechanisms of fish bodies and fins, a very widespread method is to generate a traveling body wave. The direction of flow speed is opposite to the direction of fish swimming, the same with the fish body wave. An intuitive idea is to generate a traveling body wave through multi-link rigid fitting[77]. Within this framework, the oscillating fish body is discretely constructed as a multi-link mechanism consisting of several oscillating hinge joints actuated by motors. Symmetric oscillations propel the swimmer forward straightly whereas asymmetric ones rotate the body enabling the fish to alter swimming direction. Specifically, to achieve C-start maneuvers, firstly, all joints should bend in the same direction at the same time, and all the muscles should coordinate perfectly; then, head should aim at the target precisely; later, a steady swimming gait is indispensable; and last, a closed-loop control of turning angle is needed to correct directions of swimming[78]. Liu and Hu presented a kinematic model to mimic the C-shape turning behavior and the robotic fish finally achieved the maximum turning velocity of $110^{\circ}\cdot s^{-1}$[79]. When it comes to turning control, Yu *et al.* proposed a practical method to realize various turning gaits[80]. In their method, the flexible posterior body and tail moving in the form of body wave was forcibly deflexed to ensure an asymmetric motion. That is, for the multi-joint configured robotic fish, different turning modes can be accomplished by commanding specific deflected angle in each oscillation cycle to the part or all of moving links. To pursue the better control performance, novel sensors, actuators, and mechanical structures are incorporated into the development of robotic fish. For instance, a pressure sensing system was built to heighten the adaptability of robotic fish under intricate underwater environments[81]. A monolithic Ionic Polymer-Metal Composite (IPMC) actuator-based bioinspired active fin was created to explore the twisting, bending, and flapping of robotic fish[82]. In practice, the head of the robotic fish inevitably sways while swimming due to the counterforce on the swaying tail, causing severe distortion for the image captured by the camera loaded on the head. To mitigate this problem, a cascade control system was proposed to stably track a target object, in which a camera stabilizer acted as the inner loop and an image based tracking system as the outer loop[83].

Besides trajectory approximation methods relying on body wave fitting, Central Pattern Generator (CPG) inspired locomotor controllers are growingly utilized to generate and switch a variety of swimming patterns. As a biological neural network, CPGs can be regarded as a group of coupled neurons that generate coordinated oscillatory signals in the absence of sensory inputs or descending inputs from higher cognitive elements[84,85]. A CPG could be roughly analogous to the pendulum of a clock, producing a repeating signal at a constant frequency so as to coordinate rhythmic motions. Remarkably, the CPG-based swimming control method allows easy implementation and online generation of swimming gaits. The inherent nonlinear properties of CPGs enable smooth transitions between gaits, as well as adaptations to both perturbations of state variables and modifications of control parameters. In this sense, CPGs coupled with learning algorithms and optimization techniques allow the robot to seek stable, adaptive, and versatile gaits. For example, a kinematic model of CPG-based control is widely adopted to optimize forward and backward speed of swimming[86,87] and to enhance smooth transitions between gaits with random perturbations[40]. Wu *et al.* compared kinematics differences between forward and backward swimming caused by speed, phase angle, and frequency[88]. The coupling of onboard visual perception to the CPG-based control enabled the robotic fish with multiple control surfaces to perform goal-directed swimming[89].

To circumvent the problem of tedious hydrodynamic modeling and parameter tuning, data-driven approaches are increasingly applied to motion control of robotic fish. Typically, Ren *et al.* proposed a data-driven motion control framework for a two-joint robotic fish[90]. In their method, a feedforward controller and a Proportional-Integral-Derivative (PID) based feedback controller in conjunction with a data-driven iterative feedback tuning were built to regulate speed of robotic fish in cruise and cruise in turning. Subsequently, Verma and Xu attached more importance to thrust mechanism in data-assisted modeling for speed control of robotic fish[91]. Specifically, data of pulse and step responses were collected from designated experimental trials, in which the pulse responses were employed to determine the thrust delay terms while step responses were utilized to build up the thrust nonlinearity in steady swimming. Meanwhile, a discrete-time sliding mode controller was built for speed control. Unfortunately, the proposed data-assisted model and control method was merely verified on two-joint robotic fish. More theoretical extension and experimental validation on data-driven motion control method are demanded to provide a reliable and valuable control tool for aquatic robotic systems.

4 Learning control and motion optimization

The integration of AI and control technology creates new research opportunities for bionic robotics. As two main ingredients, learning and optimization play an important role in reducing model uncertainty and improving the system performance.

4.1 Learning fishlike swimming

One of the fascinating hallmarks of an autonomous robotic system is the ability to learn and adapt new tasks and dynamic environments. As illustrated in Fig. 5, learning for motion control gives rise to different performance capabilities *via* perception-action-learning. In particular, it is possible that the adopted learning control method achieves an enhanced system performance from trial to trial by exploiting the experience gained from previous repetitions[92]. To acquire fishlike swimming, two types of learning control methods, *i.e.*, bionic learning control and Iterative Learning Control (ILC), are mainly employed.

In the bionic learning control applied to robotic fish, the basic idea is to combine the advantages of both the trajectory approximation method and the neural-based control to generate various swimming patterns. Learning rules that are extracted from kinematics of fish swimming offer adaptation mechanisms to dynamically tune the characteristic parameters. This bionic learning method provides a synthesis tool for neural-based swimming control, thereby guaranteeing the biological basis for generation of swimming gaits on the robotic fish. Typically, Hu *et al.* presented an adaptive CPG network capable of learning instructed locomotor pattern for a multi-joint robotic fish[93]. As for desired locomotor patterns in the form of teaching signals, learning rules for frequency, amplitude, and coupling weight were formulated with phase plane representation of the oscillator, which were applied to online swimming gait synthesis. Ren *et al.* proposed a General Internal Model (GIM) based learning method to learn and to regenerate coordinated fish behaviors[94]. By virtue of the universal function approximation ability and the temporal/spatial scalabilities of GIM[95], this learning method can generate the same or similar fish swimming patterns by tuning several characteristic parameters. As shown in Fig. 6, a

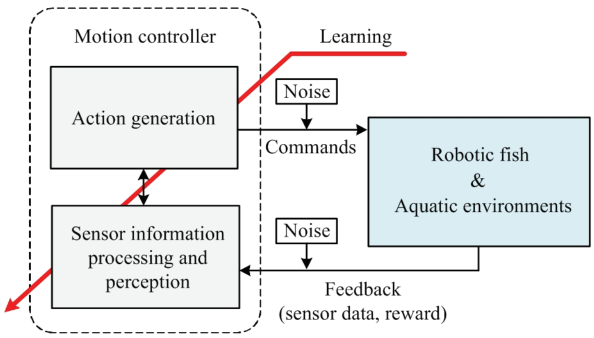

Fig. 5 Abstraction of an autonomous robotic fish system. (Adapted from Ref. [92].)

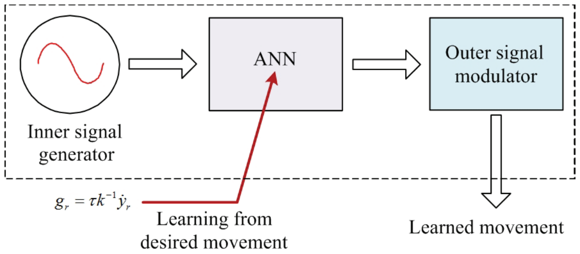

Fig. 6 Structure of the GIM.

GIM displays a basic three-component structure: an inner signal generator, an Artificial Neural Network (ANN), and an out signal modulator[96]. The internal signal generator generates a continuous-period signal as an input to the ANN. After the ANN obtains the oscillation signal from the internal signal generator, the desired motion pattern can be generated through nonlinear mapping. That is, once the desired movement y_r is given, a teaching signal for the ANN can be obtained from the outer signal modulator $g_r = \tau k^{-1} y_r$. The internal signal x is input to the ANN, while g_r is the expected output value and τ is the time constant. By learning from the training samples, the ANN can yield the expected exercise pattern. It should be noted that the learning abilities of GIM utterly depend on the capabilities of ANN as a universal function approximator[94]. Owing to the excellent function approximation ability of the ANN, which is embedded into the learning approach, the learning mechanism can easily learn these patterns. Additional advantage of the learning method is that it is able to generate similar patterns directly through the minimum changes in GIM parameters because of the scaling properties, thereby avoiding the complicated learning or training process[94].

Concerning ILC, it is generally exploited to achieve real-time control of the robotic fish and precise speed tracking performance because of its model-free property and the simplicity of the algorithm[97]. Different from the classical control technologies, such as a PID controller, ILC can use the error observations in the previous trials and update the control actions for the next trial. Hence, ILC can achieve high-precision tracking without lags in transient tracking that always exist in a PID controller[98]. A typical procedure to realize the speed tracking of robotic fish is as follows: (1) Construct a dynamical model for the multi-joint robotic fish by utilizing Lagrangian mechanics method and calculate the thrust using Lighthill's method. (2) Develop an ILC-based speed tracking scheme, e.g, by means of an input-saturated P-type ILC. It is noteworthy that the controller design need not exploit the exact model, but the system's bounded gradient information for convergence analysis. (3) Perform rigorous convergence analysis of the developed ILC scheme by applying composite energy function. Within this learning control framework, precise speed tracking and effective motion control of robotic fish have been demonstrated.

4.2 Motion optimization

Optimization is one of the most important problems in engineering practice. Owing to imprecise hydrodynamic models and strict kinematic constraints, actuating and controlling complex fish robotic systems to achieve satisfactory locomotion performance still remains challenging. A great deal of effort has been made towards improving the performance of robotic fish in terms of speed, efficiency, path planning, and maneuvering control.

As for the swimming speed optimization, major feature parameters affecting the propulsive speed are determined and optimized to maximize the speed during steady swimming. For instance, considering that the CPG parameters are closely related to the propulsive performance of the robotic fish, a method to determine relatively optimized control parameters was firstly proposed[86]. Then, a combination of dynamic model and Particle Swarm Optimization (PSO) algorithm was utilized to seek the CPG characteristic parameters for an enhanced performance. The optimized results were shown to be superior to previously report forward and backward swimming speeds. Remarkably, the robotic fish reached a top backward swimming speed of 0.51 body lengths per second, representing the best backward performance reported in the anguiform/carangiform robotic fish. Besides PSO, Genetic Algorithm (GA) was used to search optimal parameter sets for the CPG model of a multi-actuated robotic fish[99]. The obtained test results indicated that the undulatory propulsor with six fin segments was preferable due to higher speed and lower energy efficiency. In another study, the maximum velocity of the robotic fish was optimized by combining GA and Hill Climbing Algorithm (HCA)[100]. Here, GA was used to generate the initial optimal parameters of the input functions of the system, whereas HCA was further exploited to obtain near-global solution.

With respect to the efficiency optimization, the PSO algorithm and the Big Bang – Big Crunch (BB–BC)[101] algorithm are usually used. By choosing the particle swarm size and number of iterations in the PSO algorithm, the optimal parameter set of CPG and the optimized propulsion efficiency were obtained[86]. Another way to optimize propulsion efficiency is to use BB–BC algorithm, a global optimization method inspired from one of the cosmological theories known as closed universe. The BB–BC algorithm was adapted to optimize the link length for a four-link carangiform robotic fish, producing optimum link lengths and endpoints of each joint in forward swimming and turning[102]. Numerical results indicated that link length optimization could improve the propulsion efficiency of the robotic fish.

Path planning is essentially defined as the problem of finding a safe and efficient collision-free path of one or more rigid objects from a given start to a known target configuration. In the path planning optimization of robotic fish, to alleviate the intrinsic computational complexity, several heuristic approaches together with computational intelligence have been developed. In practice, GA is widely applied in obstacle avoidance of mobile robots due to its versatility, robustness and easy to get into local optimum. Therefore, the grid based path modeling method and the GA-based path optimization are combined to produce an optimal or suboptimal swimming path for the robotic fish. In a more complex path planning case involving multiple robotic fish and goals, a Multi-Objective Cooperative Co-Evolution Algorithm (MOCCEA) is usually used[103]. Essentially, MOCCEA simulates the co-evolution mechanism among different species in nature. The single-objective co-evolution model is expanded into a co-evolutionary multi-objective model, which can effectively match the evolutions of multiple populations, thereby solving complex optimization problems. Under the premise of ensuring higher path smoothness, Yang and Jiang used MOCCEA to find an optimized solution for path planning of multiple robotic fish[104]. Specifically, partial subsets were heuristically generated as a result of considering initial yaw angle of robotic fish and its swimming characteristics. Thus, MOCCEA settled the problem of turning round during path planning and realized coordinated motions among multiple robotic fish. Simulation results demonstrated that the MOCCEA- based method achieved shorter average path length and higher average path smoothness than the NSGA-II- based method.

Regarding the maneuverability optimization, the two primary concerns are acceleration and steering characteristics[105]. In the context of predator-prey systems, pursuing fast and precise C-starts is a critical survival skill for live fish. Su *et al.* optimized the maneuvering control of fast C-starts of a multi-joint BCF-type robotic fish[106]. Specifically, the steering speed was maximized by finely designing the preparatory phase and the propulsion phase, while the relatively accurate steering angle was achieved by the closed-loop control strategy in the propulsion phase and in the variation phase. The robotic fish performed C-starts flexibly with a turning angle of up to 213˚, a top turning rate of approximately $670^\circ\cdot s^{-1}$ measured by the onboard gyroscope, as well as an upper limit of turning precision of less than 10˚. These optimized results were shown to be superior to previously reported turning rate and turning precision.

5 Motion coordination of multiple robotic fish

Besides offering propulsion solutions in aquatic environments, fish that swim in an organized and planned way provide valuable sights into alternative strategies for designing nature-inspired algorithms and engineering multi-fish systems. In this section, Artificial Fish School Algorithm (AFSA) and some coordination control of multiple robotic fish will be briefly reviewed and analyzed.

5.1 AFSA

As a bionic swarm intelligence algorithm, AFSA draws inspiration from collective movement of the fish and their various social behaviors [37]. This algorithm focuses on the fish groups who have no leader and communicate with the surrounding fish about the feedback information of the environment to swim. Based on the mathematical model of artificial fish, which is a fictitious entity of true fish used to carry on the analysis and explanation of problem, description equations for a series of actions such as fish praying, swarming, following, moving, and leaping can be obtained. The behaviors of fish depend on the current state of itself and the state of the environment. Thus, AFSA has the ability to solve complex nonlinear high-dimensional problems, allowing parameters to be properly adjusted. In brief, owing to high convergence speed, flexibility, error tolerance, and high accuracy, AFSA has been widely used for solving various complex optimization problems, such as control, image processing, data mining, improving neural networks, scheduling, and signal processing[37].

However, AFSA also suffer several drawbacks, including higher time complexity, lack of balance between global search and local search, and without use of the experiences of group members for the next movements. To compensate the disadvantages of standard AFSA, many improvements have been implemented over the past decades. For example, a cultured artificial fish-swarm algorithm, *i.e.*, a novel cultured AFSA with the crossover operator, was developed. It has faster convergence speed and overcomes the weakness of blind searching for global optimum value via a great number of experiments. Aiming to improve the algorithm's stability and the ability to search the global optimum, Wang *et al.* proposed an improved AFSA algorithm. When the artificial fish swarm's optimum makes no difference with defined generations, leaping behavior is triggered and the artificial fish parameter is altered randomly, thereby increasing the probability of obtaining a global optimum solution[107]. Fernandes *et al.* performed global optimization for fish movements, finding food, leaping, and other social actions[108].

To improve the optimization capability, there have been several attempts to combine the AFSA with other optimization methods like PSO, fuzzy logic, cellular learning automata or intelligent search methods like tabu search, simulated annealing, and chaos search[37]. For instance, combining PSO with AFSA, the PSO-AFSA method takes advantage of the rapid convergence ability of PSO and the strong global searching ability of AFSA to offer more desirable optimized results. Jiang *et al.* demonstrated the efficiency of the PSO-AFSA method in underactuated autonomous underwater vehicle control parameter optimization[109]. Shuffled Frog Leaping Algorithm (SFLA) finds global extremum slower and easily falls into local extremum. Therefore, combining SFLA with AFSA can accelerate the optimization speed and avoid falling into local extremum[110]. Hu *et al.* demonstrated that the running speed of the AFSA based on GPU was 30 times faster than the AFSA based on the CPU[111].

5.2 Coordinated control of multiple robotic fish

In the context of a multi-robot system, when coordinating in unstructured or dynamic aquatic environments, it is expected that a group of robotic fish with a relatively simple function is able to accomplish complex missions that exceed the capabilities of one individual. The significance of the multiple robotic fish coordination is twofold. On the one hand, robotic fish-based coordination system offers a viable solution to complex underwater missions, which are intractable for one individual or tough to be fulfilled by other underwater robots. On the other hand, with the aid of a school of bionic robotic fish, in addition to provide valuable information for fisheries science, the schooling behaviors of fish in nature can be recorded and better understood. At present, there are basically two types of coordination systems, centralized and decentralized, which differ in the way they use sensor information.

In the centralized multiple robotic fish coordination, centralized control is generally utilized. Since the used robotic fish have no ability of self-positioning, an overhead global vision is responsible for acquiring information of the environment and the states of the fish. As shown in Fig. 7, a multiple robotic fish coordination platform can roughly be decomposed into four subsystems: an image capturing subsystem, an information processing & decision-making subsystem, a communication subsystem, and a robot subsystem[36,112]. More specifically, an image of the pool is captured by an overhead camera and sent to the upper computer every 40 ms. Then in the upper computer, the image is processed effectively to estimate the pose information of the robots. After making a series of decisions, through the wireless communication module, the upper computer not only sends control commands to the robots such that

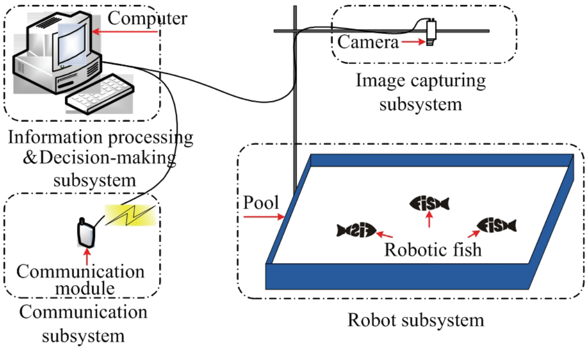

Fig. 7 Schematic of multiple robotic fish coordination platform.

the robots can adjust their locomotion modes, but also receives the feedback from the robots. Hence, a complete control loop is implemented. In practice, hierarchical control algorithms for cooperative tasks are usually adopted, which are ultimately decomposed into two primitive motion controllers, *i.e.*, speed controller and orientation controller. For example, Yu *et al.* proposed a hierarchical architecture for an artificial multi-fish system which consists of five levels: task level, role level, behavior level, action level, and controller level, to formalize the processes from task decomposition, role assignments, and control performance[113]. A competitive game between three automatic fish and a manually controlled fish was performed to validate the effectiveness of the adopted coordination framework. Zhang *et al.* proposed a coordination method for multiple robotic fish in underwater transport task[114]. Synthesizing the kinematic constraints of the robotic fish and the dynamic characteristics of the aquatic environment, they used the limit cycle approach for pose control and collision avoidance, and the fuzzy logic method for orientation control. Jia and Wang investigated the distributed leader–follower cohesive flocking problem and the distributed leader–follower formation flocking problem of multiple robotic fish governed by extended second-order unicycles[115]. Based on the combination of consensus protocol and potential function, a distributed cohesive flocking algorithm was designed for the one-leader and multiple-follower robotic fish system. Yu *et al.* combined behavior-based hierarchical architecture with fuzzy reinforcement learning to accomplish effective coordination in water polo game[116]. Noticeably, since October 2007, this multiple robotic fish coordination platform has been successfully applied to international underwater robot competitions to promote innovative research and education in underwater robotics.

Although the centralized method can produce optimal coordination, it tardily responds to external changes and is vulnerable to the failure of central planning. More seriously, the centralized method for multiple robotic fish coordination is infeasible in true oceanic open waters since global visual information gathering becomes unavailable. To over these drawbacks, decentralized control of multiple robotic fish coordination has been investigated. Apparently, in the decentralized multiple robotic fish coordination, the single robotic fish should have a certain degree of autonomy, allowing coordinated plan based on local observations. Hu *et al.* firstly developed a vision-based autonomous robotic fish capable of 3D locomotion, and presented a decentralized control method in target-tracking and collision avoidance task for two robotic fish[117]. Afterwards, they further investigated the box-pushing task using three autonomous robotic fish equipped with a monocular camera[118]. Their solution was based on a division-of-labor approach that decomposes the task into an observing subtask and two pushing subtasks. The subtask consisted of a series of behaviors, each designed to fulfill one step of the subtask. The robotic fish coordinated through explicit communications and distributed the subtasks with a market-based dynamic task allocation method. Fig. 8 shows a typical experimental scenario of the coordinated box-pushing using three robotic fish. Ryuh *et al.* built a multi-agent robotic fish system together with buoy robots for mariculture monitoring, in which multiple autonomous robotic fish were deployed to collect marine information such as water temperature and pollution level[119]. It should be remarked that the achieved real-world coordination tasks by existing robotic fish are rather limited due to the limited communication, positioning, and endurance of the single robotic fish. In addition, the self-organizing mechanisms of fish can be emulated and verified with multiple robotic fish coordination system, offering insights into distributed system executions and applications. For instance, Jia and Zhang discussed a distributed leader-follower flocking problem of multiple robotic fish governed by extended second-order unicycles[120]. Wang *et al.* examined distributed control laws for formations of swimming

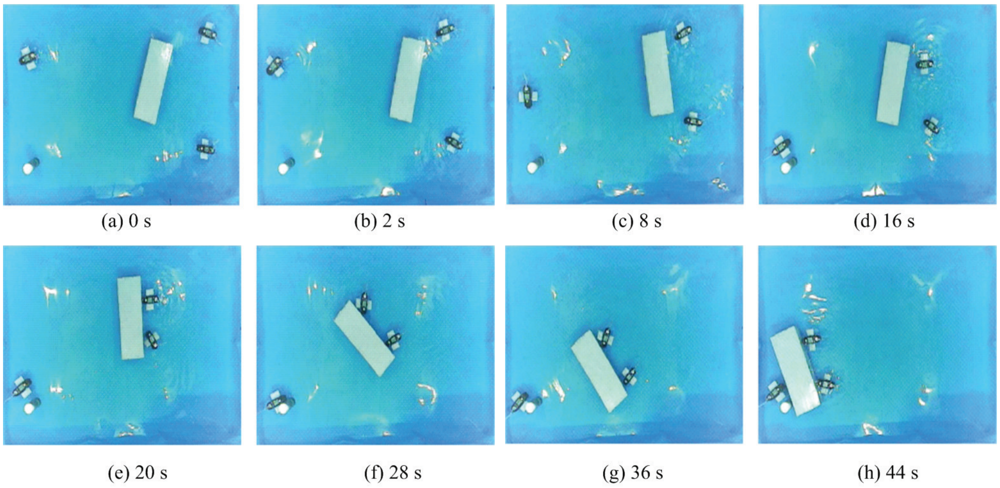

Fig. 8 Experimental scenario of underwater box-pushing through three robotic fish. (Adapted from Ref. [118].)

robotic fish generating antiphase sinusoidal body waves[121]. More interestingly, Wang *et al.* in another work used the robotic fish to investigate how personality traits evolved and effective leadership emerged in a group during increasingly difficult tasks[122,123]. Similar research results on robotic fish groups may provide insights both for creating new robotic systems and for better appreciating the organic self-organization of social animals. In recent years, bionic robotic fish is increasingly utilized as a new tool to interact with live fish for investigating social behaviors in fish group. For example, Swain *et al.* presented a new cyber–physical implementation in which the robotic fish can adopt real-time feedback to adjust the motion in response to live fish and other environmental features[124]; Marras and Porfiri employed a robotic fish and individual golden shiners to swim together in a water tunnel at different flow velocities and revealed that the biomimetic locomotion of the robotic fish was a determinant of fish positional preference (see Fig. 9)[125]; Bonnet *et al.* studied the collective decision-making by a group of autonomous robots and a group of zebrafish, leading to a shared decision about swimming direction and further demonstrated the possibility of creating mixed societies of vertebrates and robots in order to study or control animal behavior[126].

6 Summary and outlook

In this paper, we have presented a survey of existing works on bionic robotic fish with particular emphasis on motion control and motion coordination aspects. Specifically, the state-of-the-art hydrodynamic modeling and testing, kinematic modeling and control, learning and optimization, as well as coordination control are sequentially reviewed. As a hybrid topic closely combining bionics with robotics, this paper provides perspectives on modeling and control of bionic robotic

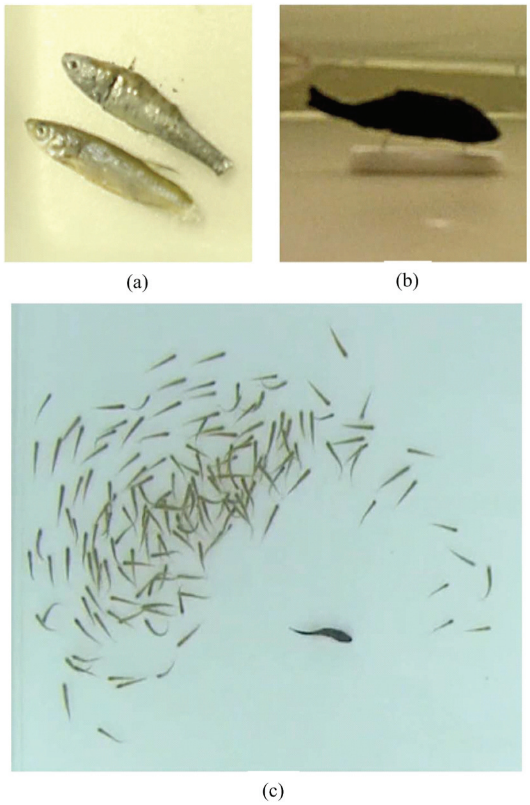

Fig. 9 Experimental scenario of interaction between robotic fish with fish groups. (Adapted from Ref. [125].)

fish, especially in the background of AI, robotics, and machine learning which are advancing at a rapid pace. To provide insights into in-depth research and development of bionic robotic fish, we make an attempt to distill some critical issues and promising research directions listed below.

Firstly, benefiting from continuous improvements in mechatronic design, motion control, and sensors, bionic robotic fish have been developed rapidly in the past two decades. They are able to swim faster and faster, turn more and more agilely. However, there is still considerable gap on swimming performance between bionic robotic fish and real fish. For instance, muskellunge can explosively perform a fast-start behavior with a peak angular velocity up to 2500 $^\circ\cdot s^{-1}$[127]. By contrast, exiting robotic fish only realizes a fast-start as high as 670 $^\circ\cdot s^{-1}$[106]. This is only a wide gap in horizontal plane. In 3D space, muskellunge is able to utilize its pectoral fins for a fast and accurate predatory behavior. However, the existing robotic fish only exhibits some simple 3D maneuvers, like diving, surfacing, and rough 3D turning. More delicate pectoral structures and more practical closed-loop control methods are needed to enhance the motion capability of the bionic robotic fish. Therefore, in the future studies, how to create a delicate pectoral structure, how to cooperate the pectoral fins and fish body as well as the caudal fin, how to perform integrated structure-control optimization according to a single objective or multiple objectives (*e.g.*, speed, efficiency, maneuverability, and energy consumption)[128], are key to achieving fast and accurate 3D maneuvers.

The second challenging issue for bionic robotic fish is underwater environmental perception. Future application of the bionic robotic fish will require them swim in unknown and unstructured underwater environments. To this end, the capability of the robotic fish to sense the underwater environment is essential. Most existing researches tend to concentrate on the motion control, and much less attention is paid to underwater environment perception. There is no denying that the perceptual ability of the robotic fish is very limited. For example, some vision sensors are employed to detect and avoid obstacles[26,129]. These sensors require high demands for the underwater environment, like clearity, lightness, and no turbulence. In the meantime, inspire by fish's lateral lines, some artificial ones are designed to detect water pressure, even flow direction[130]. But there is still a long way to go for the large-scale real-world applications. Besides, due to the undulatory propulsion, head yawing is an essential feature for the robotic fish, which will cause the swing of the sensor data. As far as precision is concerned, exclusive multi-sensor data fusion methods are demanded. Thus, the bionic robotic fish can effectively percept the underwater environment with a wealth of sensor information.

Third, the question of how to enhance the intelligence is another challenge. At present, AI is one of the fastest growing fields of technology, allowing a wide range of augment ability and applicability in robotics and automation. Although it may be too hasty to apply AI in bionic robotic fish, enhancing its intelligence is very necessary. After all, actual underwater environments are usually complex, harsh, and even dangerous, higher intelligence can substantially enhance the survival of the robotic fish. The self-learning capability is firstly emphasized. Reinforcement Learning (RL) provides an excellent framework. Learning from the interaction with environment is probably a fundamental idea underlying all the theories of learning and intelligence[131]. As for the bionic robotic fish, a great deal of environmental information can be utilized to guide its action, when various underwater sensors are equipped. Combined with the experiences, the robotic fish can evolve a much more excellent behavior in complex underwater environment. Although some studies have been focused on the application of RL in robotic fish[132,133], how to develop the learning algorithms appropriate for dynamic underwater environments, like a policy, a reward signal, and a value function is worthy of in-depth investigation. In this sense, the level of autonomy and adaptability of future robotic systems will be increased.

Fourth, prominent locomotion capability can hardly be attained without powerful actuation system. Now, most high-maneuverability robotic fish employ DC motors or servomotors as the main actuation system[134–136]. The powerful driven capability of the DC motor can effectively improve the maneuverability of the robotic fish. Besides, other materials such as IPMC, shape memory alloy, artificial muscle, nanometer material can also be utilized to a variety of different types of bionic robotic fish[53,137]. For example, Jusufi *et al.* employed actively controlled pneumatic actuators attached to a flexible foil to explore the undulatory locomotion and mechanisms for robotic fish body stiffness control[138]. Remarkably, a soft robotic fish with a soft continuum body for close-up exploration of underwater life was reported[15,139]. Based on a fluidic elastomer actuator, this soft robotic fish successfully realized escape maneuvers with a peck angular speed up to 300 $^{\circ}\cdot s^{-1}$. Although its turning speed is slightly lower than a motor-driven one's, the soft robotic fish provides a bioinspired design paradigm[140]. Compared with other materials, fluidic actuator has many advantages, such as high speed, light weight, and strong explosive power, which is crucial for underwater robots. At the same time, a variety of soft actuators have been successfully applied in different robots, revealing sufficiently powerful and reliable characteristics[141,142]. Therefore, it is hopefully to produce a series of technological solutions that can constitute the building blocks of future advanced robots.

Lastly, the coordination control of multiple robotic fish system is still an active and challenging topic today. From the engineering perspective, homogeneous, heterogeneous, and conjoint multiple robotic fish systems can offer efficient and agile solution to various underwater operations. For example, in naval reconnaissance task, multiple robotic fish can improve the performance of the task execution by sharing collected information while reduce the possibility of detection by pretending to be a real fish school. From the science perspective, the self-organizing mechanisms of fish school and interaction principles among fish may offer insights into accomplishing team tasks. Because of the undulatory characteristic of the bionic robotic fish, how to make the task allocation and scheduling, how to navigate autonomously in unknown and changing environments, how to improve the existing multi-objective control algorithms are becoming critically important to break through the application bottleneck of multiple robotic fish system. Certainly, some swarm intelligence algorithms or strategies shed light on the creation of new coordinated control methods and can be applied in the robotic fish group in the future[143,144]. Furthermore, AI also provides a powerful new tool for coordination control of multiple robotic fish. Depending on excellent learning capability of AI, the multiple robotic fish can learn executable models of behavior from the observation and experience. Meanwhile, AI can also be utilized for task planning and decision-making in the multiple robotic fish coordination, since AI is adept in the core strategy issues in complex missions.

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