Maneuverable Gait Selection for a Novel Fish-Inspired Robot Using a CMAES-Assisted Workflow

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Abstract. Among underwater vehicles, fish-inspired designs are often selected for their efficient gaits; these designs, however, remain limited in their maneuverability, especially in confined spaces. This paper presents a new design for a fish-inspired robot with two degree-of-freedom pectoral fins and a single degree-of-freedom caudal fin. This robot has been designed to operate in open-channel canals in the presence of external disturbances. With the complex interactions of water in mind, the composition of goal-specific swimming gaits is trained via a machine learning workflow in which automated trials in the lab are used to select a subset of potential gaits for outdoor trials. The goal of this process is to minimize the time cost of outdoor experimentation through the identification and transfer of high-performing gaits with the understanding that, in the absence of complete replication of the intended target environment, some or many of these gaits must be eliminated in the real world. This process is motivated by the challenge of balancing the optimization of complex, high degree-of-freedom robots for disturbance-heavy, random, niche environments against the limitations of current machine learning techniques in real-world experiments, and has been used in the design process as well as across a number of locomotion goals.

The key contribution of this paper involves finding strategies that leverage online learning methods to train a bio-inspired fish robot by identifying high-performing gaits that have a consistent performance both in the laboratory experiments and the intended operating environment. Using the workflow described herein, the resulting robot can reach a forward swimming speed of 0.385 m/s (0.71 body lengths per second) and can achieve a near-zero turning radius.

Keywords: Fish-inspired robot, Gait selection, Maneuverability, Evolution strategy, Pectoral fins, Training workflow, Experimental training

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1. Introduction

The challenge of underwater robotic locomotion is a complex phenomenon depending on the timed interactions between water and an robot's swimming surfaces. Though engineered solutions for swimming robots are often inspired by nature, characterization of these systems often occurs in ideal laboratory environments where the water column is controlled and well characterized. Based on the necessity to create repeatable and controlled conditions, ideal swimming gaits are often constructed using either analytic fluid dynamic models or from data in controlled experimental environments. Studying robots in these conditions, however, can negatively impact the ability of optimized robotic swimmers to achieve similar performance in real-world environments, where disturbances and variation are uncontrolled. Thus, the majority of robotic fish that have been developed are rarely optimal for swimming in real world environments. Some notable exceptions include [1, 2].

Having evolved over millions of years, fish and other aquatic animals have solved the problem of operating in variable conditions through a wide range of adaptations that endow them with the ability to swim with high efficiency, speed, and agility [3–5]. The sheer number of different fish species in the world (two to three thousand Cichlids alone [6]) demonstrates that each permutation of the many swimming styles, body layouts, and relative scales of swimming surfaces seen in these species successfully balances certain needs of that species within its niche.

Transferring biologists' understanding of how fish and other swimmers utilize one or more swimming strategies is one approach researchers use in dealing with real-wold conditions. Research has focused on caudal (tail) and pectoral fin design, as these fins are the primary generators of thrust in biological fishes [7, 8]. Various forms of rigid [9–11], multi-body [12–22] and soft [2, 23] caudal fins have been studied in order to emulate this propulsion system. Recent studies show that soft caudal fins produce more effective vortices compared to rigid fins while being significantly simpler than multi-bodied ones [2]. Carangiform fish propulsion is also achieved by leveraging exchange of momentum between robot's body and fluid vortices without requiring external fins [11, 24]. Soft fabrication techniques have been also employed successfully in many robotic fish [2, 23, 25–29]. Mechanisms have been built to emulate the role of pectoral fins of fish in locomotion [30], because these multipurpose fins provide various forms of flapping, rowing, and cupping motions, each of which are used in a variety of swimming scenarios [7, 31]. The complexity of these fins can vary widely across species [30]; complex pectoral fin mechanisms have been constructed to study their role in biological underwater locomotion [7, 8], and have been integrated – in simplified form – in robotic systems alongside caudal fins for gliding, diving, depth control, thrust generation [2, 4, 9, 32–36]. In the majority of cases, however, these robotic fish have not been trained and tested in environments other than ideal lab conditions. We believe that the high repeatability associated with ideal test

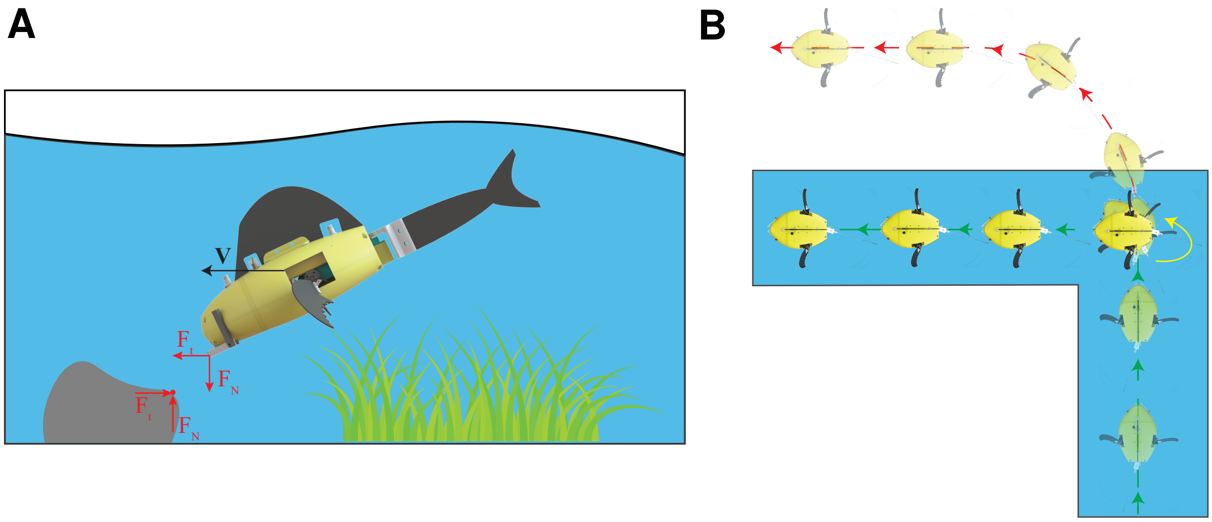

Figure 1: **Conceptual illustration of maneuvering and interaction criteria in developing a robotic fish for performing tasks. A:** Capability of interacting with environment while swimming. **B:** Maneuverability in tight spaces (Green arrow: Forward swimming using caudal fin. Yellow arrow: Successful low radius turning using pectoral fins. Red arrow: Failed high radius turning using caudal fin).

environments can negatively impact the robot's performance and its capability to perform tasks in the real world. In this paper, we show that non-ideal experimental setups with uncertainties embedded in them, when utilized in conjunction with machine learning techniques is useful to experimentally search for optimal gaits that can be used across different environments.

Instead of utilizing model-driven techniques for optimizing gaits from experimental data, research has also investigated the use of machine learning and artificial intelligence techniques for directly obtaining optimal swimming gaits and control strategies. Two methods of bionic learning control and Iterative Learning Control (ILC) have been mainly employed in learning fishlike swimming. The objective in bionic control is to combine the advantages of both trajectory approximation and neural-based control in order to generate different swimming patterns [37–39]. ILC is mainly used to achieve real-time control of robotic fish due to the simplicity of the algorithms with model-free properties [40]. Motion optimization is used widely throughout robotics to improve locomotion performance. This method is used toward improving the performance of robotic fish in terms of speed, efficiency and maneuvering control [3]. Different algorithms have been used by roboticists for motion optimization. For example, a combination of dynamic model and Particle Swarm Optimization is used in [41], while Zhou *et al* use a Genetic Algorithm (GA) to optimize undulatory swimming gait parameters for a fish robot [42]. The maximum swimming speed of a robotic fish was obtained by applying a combination of a GA and Hill Climbing Algorithm [43]. Again however, many of these approaches have only been utilized or evaluated in laboratory settings rather than more lifelike conditions.

To provide insights into the challenges addressed above, this paper describes Fish-Inspired Robot for Extreme Environments (FIRE), a robot intended to navigate within an open canal system for the purposes of clearing underwater vegetation. In order to achieve defined tasks, the robot has been designed to orient its body independent from generating forward thrust in order to simplify control and motion planning issues that would normally arise if they were coupled. The size constraints of our target underwater environment and the remote nature of the work to be done also play an important role in the design. To expand the robot's capabilities and maneuverability, we have implemented a more complex mechanism in the pectoral fins. Because of the limitations of learning in a single environment, we also discuss a learning-based training and searching workflow for identifying locomotory gaits that survive the transfer between lab-based trials and secondary, target environments. This has been used to generate a number of swimming strategies and can be expanded to assist in the design of the robot itself.

Our current study focuses on the design, manufacturing, system identification, and finding methods to obtain the high performance gaits that are applicable across different uncertain environments. These are critical parts of the greater challenge of developing a robotic fish that is capable of self-navigating and autonomously performing tasks in the field. This effort has been made in the context of a recent funded collaboration with a local water utility in the Phoenix metropolitan area; the long-term goal of the project is to use autonomous robots to navigate along narrow open canals for the purposes of cutting vegetation or scrubbing surfaces (figure 1). This requires new capabilities not easily found within existing literature: the ability to navigate narrow, open channels while exerting forces with an end-effector on the sloped sides and shallow bottom of a waterway. Though these challenges represent a longer-term set of achievements than are presently solved, they require strategies for efficiently learning new actions within defined settings and then testing transferred knowledge in target environments in a way that balances the costs and limitations of testing in both environments.

1.1. Contributions

This paper sheds light on not only the design, manufacturing and system identification of the robotic fish, but also applies learning-based training and searching method to obtain the high performance gaits that are applicable across different uncertain environments. The contributions of the paper may be summarized as follows: we introduce (i) a pectoral fin mechanism design based on a 2-DOF spherical mechanism facilitated by laminate design concepts that minimizes manufacturing costs typically associated with spherical, parallel mechanisms. (ii) A design for a fish-inspired robot, which combines one caudal and two pectoral fins. The resulting five

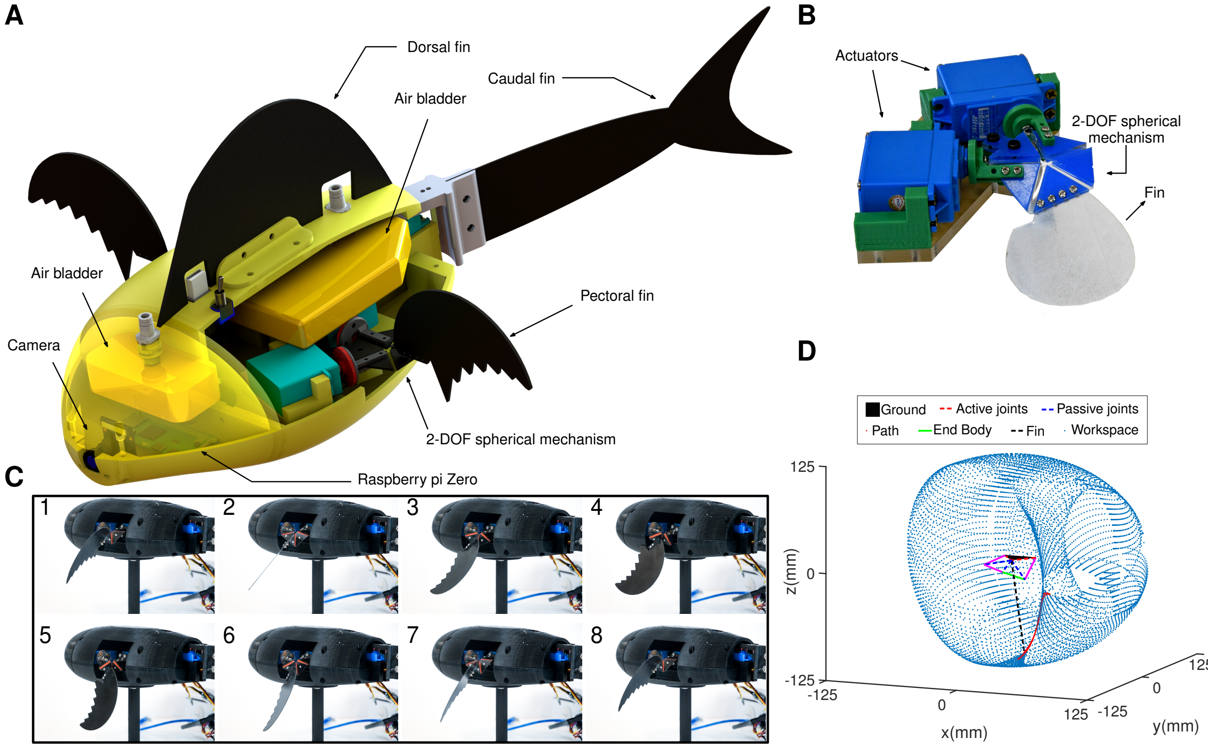

Figure 2: **FIRE, the souckermouth catfish-inspired robot.** **A:** System overview. **B:** 2-DOF spherical mechanism exploited in FIRE's pectoral fins which is built by using laminated techniques. **C:** Extracted frames of a pectoral fin's propulsion for turning (result of training in pectoral fin's attachment selection). **D:** Schematics of the pectoral fin's 2-DOF spherical mechanism, its workspace (blue dots), and end-effector path in previous motion (red dots).

degrees of freedom may be described with a complex, high-dimensional set of locomotion/gait parameters. To reduce this complexity, we have also (iii) developed strategies for identifying high-performing sets of these gait parameters with an online learning strategy (CMA-ES). Our lab setup often differs from the intended goal environment in key ways (perturbation, water speed, type of data-collection setup, i.e., force instead of trajectory). This has also led us to (iv) develop strategies for finding gait parameter sets that have high performance when tested in the lab and the intended operating environment. These efforts have resulted in a design and optimization workflow for robots that works well in niche environments, while permitting the majority of development, data collection, and characterization to be done in the lab.

2. Fish-inspired Robot for Extreme Environments.

In this study, we have developed and trained a robotic fish capable of swimming in extreme environments (figure 2A). The robotic fish propels itself by using its pectoral and caudal fins.

2.1. Design and manufacturing of robotic fish

FIRE is inspired by the suckermouth catfish (Plecostomus) due to the similar of this fish's biological niche with our target environemnt. These benthic, bottom-dwelling creatures have wide, flat bodies, and are evolved to live in high-current streams and swim along surfaces to feed while avoiding higher mid-stream currents.

In designing the robotic fish body, we have reserved space for electronics, a swim bladder for buoyancy, and a sensor suite. At this stage, the bladder is inflated prior to deployment in order to set the fish in a neutrally-buoyant state. We have embedded three types of fins evocative of a catfish's pectoral, caudal and dorsal fins. While two sets of pectoral fins are laterally placed in the center of the robotic fish, its caudal fin is placed at its posterior (figure 2A). A passive dorsal fin is located on the top of the robotic fish to resist body rotation due to caudal fin motion.

2.2. Pectoral fin: 2-DOF mechanism

We have designed and constructed a 2-DOF spherical parallel mechanism (also known as a 5-bar mechanism) to move the pectoral fins (figure 2B). The advantage of using this parallel mechanism is that the actuators are mounted within the body as opposed to a serial mechanism design; this reduces the torque requirements of our servos while simultaneously permitting a more compact, lower-drag design. This spherical mechanism has been scaled down via laminate fabrication techniques, whose benefits are discussed below. The mechanism is designed to be flat in its neutral state and uses a symmetric design in which the angles between all joins are 72 degrees. This flat, symmetric design permits a more compact design (as opposed to its most popular implementation of this mechanism [44]) as well as enabling us to attach and evaluate a two-body fin.

The two degree-of-freedom mechanism used in FIRE uses laminate techniques for creating a spherical five-bar linkage. Laminate devices are typically manufactured by an iterative process whereby a number of different flat materials are individually cut and laminated together to create a traditional kinematic mechanism connected by flexure joints. This process has a number of benefits. A number of design variations may be rapidly produced, permitting design variations to be analyzed quickly; second, the low-cost of materials means that such devices can be reproduced quickly and at lower costs than traditional linkages, making this device design compatible with our goal to deploy a low-cost "school" of robotic fish for maintaining water canals.

3. Training the Robotic Fish

This section covers the process of training the robotic fish. We first present the proposed workflow of training the robot. Then, we discuss the experimental setup and the optimization algorithm that has been used in the training. Finally, we cover leveraging the experimental training in selecting the pectoral fin attachments.

3.1. Training Workflow

The process of training FIRE comes with challenges due to its multi-fin design and the high number of gait parameters required to enumerate a gait. Its intended functionality is to be used in the maintenance of water canals with a width of as low as 3 feet; these canals have high currents and perturbations due to irregular flows as well as obstacles. In order to train the robotic fish to maneuver in this environment, a training workflow has been proposed to find gait parameters in presence of perturbation. To the knowledge of the authors, FIRE is the first robotic fish to be trained in an environment where there exists perturbation and reflected waves with amplitudes comparable to the robotic fish's height;

Figure 3A highlights a workflow we have used to balance the competing needs of testing in a repeatable environment while learning how our device will operate in more realistic settings. This is informed by the current state and limitations of learning algorithms and the time and resources needed to learn motion patterns for complex, high-dimensional systems. We next describe three steps of the proposed workflow:

Experiment Design: The first segment of our workflow, experimental design, consists of (i) Selecting a training algorithm and designing the experimental setup, (ii) Formulating gait motion parameters and desired goal performance, and (iii) Introducing possible constraints and relations to reduce and simplify the high dimensional parameter space. We have selected a machine-learning-based approach towards selecting robust gaits; while the whole space may be searched for lower-dimensional spaces, we utilize the Covariance matrix adaptation evolution strategy (CMA-ES) as a way to find ideal parameters in higher dimensional spaces, in which finding global optimal solutions through spanning the space is nearly impossible.

Motion gaits are formulated using sinusoidal patterns. This makes it possible to create motion commands with a small number of parameters, simplifying the training process. The

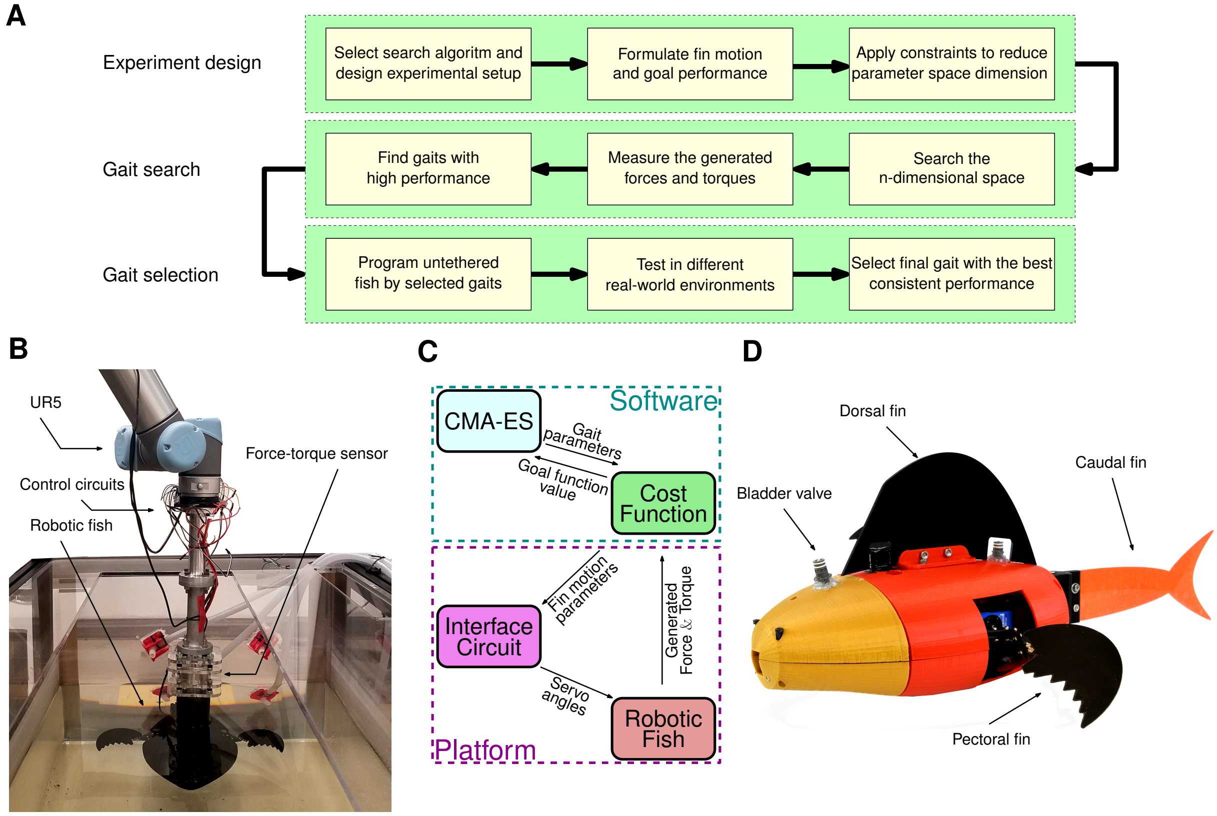

Figure 3: **FIRE's training workflow.** **A:** Workflow proposed for training FIRE. **B:** The experimental setup. **C:** Experimental implementation of on-line CMA-ES algorithm. **D:**The untethered FIRE.

servos' command signals are defined as:

$$\begin{aligned}
\text{Right pectoral fin:} \quad & \theta_1 = \beta_1 + \alpha_1 \sin(2\pi f_1 t) \\
& \theta_2 = \beta_2 + \alpha_2 \sin(2\pi f_2 t + \phi_1), \\
\text{Left pectoral fin:} \quad & \theta_3 = \beta_3 + \alpha_3 \sin(2\pi f_3 t) \\
& \theta_4 = \beta_4 + \alpha_4 \sin(2\pi f_4 t + \phi_2), \\
\text{Caudal fin:} \quad & \theta_5 = \beta_5 + \alpha_5 \sin(2\pi f_5 t)
\end{aligned} \tag{1}$$

where θ_i is actuators' angles and β_i, α_i, ,f_i , and ϕ_i are the sinusoidal signals' angular offset, amplitude, frequency and phase shift, respectively. There are 17 parameters to control the maneuver of the robotic fish fins. To evaluate the performance of each parameter, we measure forces and torques as the primary criteria for evaluating robotic fish performance, as in [7, 45].

Gait Search: The goal of this segment of our workflow (figure 3) is to perform a smart search through the n-dimensional space of parameters while evaluating the performance of each set of gait parameters. In training FIRE, we measure the generated torque and forces by fin propulsion in the presence of nonuniform vortices in the water tank. Since these vortices can randomly affect thrust generation, tests are typically repeated for each set of parameters to minimize this effect. The sampling times for each test have been calculated based on the propulsion frequency (period), the range of the UR5's path, and velocity of the UR5's end-effector. By varying the sampling frequency we can maximize the number of gait cycles within the limited range of a single test. The speed of the UR5 is also limited to 0.1 m/s during fin-based locomotion trials and 0.6 m/s when the fins are not actuated.

We believe this experimental approach pairs well with machine learning because it injects random, unmeasured, unmodeled noise into each trial; this would be difficult to anticipate in a CFD-based optimization. We contend that this helps prevent over-fitting to a specific set of initial conditions which must be known a priori, and generates more robust solutions.

Gait Selection: The goal of this portion of the workflow is to find a set of gait parameters that repeatably perform well against a user-supplied performance objective over many cycles in different situations. Though we prefer to perform testing in the lab, the fish must ultimately be able to perform a variety of specialized maneuvers, including turning, diving, and swimming upstream in a canal where perturbation and current are present. To achieve this objective, the performance of any selected gait must, therefore, have high performance both in the laboratory experiments and the real-world across many different locomotion goals. Hence, our workflow evaluates more than one top-performing gait for a given maneuver using the untethered FIRE (figure 3D). In other words, for each swimming maneuver, the top performing gaits found in CMA-ES search algorithms have been selected as candidates to be evaluated in the free-swimming robot. The gait with consistently high-performing swimming across lab/outdoor environments is then selected for each swimming maneuver. The best gait must satisfy two criteria in all environments. The robot's observed motion must first be consistent in both environments for each desired maneuver; the gait must also exhibit the highest performance across all tested gaits (when evaluated by the same cost function used in the initial gait search). For example, for the selected 'Turning' gait (Sec. 4.1), the gait reported as the highest performing gait exhibited consistent, pure turning motion, and its turning speed was highest among all tested gaits in both environments (pool and tank).

Table 1: The tuned parameters for the CMA-ES algorithm.

Parameters	**Value**	**Parameters**	**Value**
Population size	60	Number of effective solutions	16.57
Number of variables	6	Initial step size	0.67
Maximum iteration	$1,000$	Step size dampening	2.66
Number of parents	30	Learning rate	0.36

3.2. Experimental setup

3.3. Covariance matrix adaptation evolution strategy

Evolution Strategy (ES) algorithms are optimization techniques considered as practical alternatives to gradient-based methods which suffer from converging to local optimal solutions [46]. The Covariance Matrix Adaptation Evolution Strategy is a type of ES algorithms, known as a stochastic method for numerical optimization of nonlinear and non-convex optimization problems [47]. Using the CMA-ES in practical experiments has many advantages in comparison with other metaheuristic and search-based algorithms since it is known to have enhanced convergence speed. These practical benefits include increasing the service life of motors, bearings, and gears that can become worn or damaged during training. On the other hand, the main disadvantage of the CMA-ES is its computational complexity which is originated from the covariance matrix self-adaptation and decomposition in this algorithm [48]. In the recent, similar study conducted in [49], the CMA-ES algorithm has been employed to optimize the controller for travel speed control of a Knifefish-inspired soft robot. They used this algorithm due to its short evaluation time compared to other evolutionary strategies. Using the CMA-ES algorithm to improve convergence rates can have practical benefits in robotic systems, including increasing the service life of motors, bearings, and gears, which can be overloaded during training.

In our experimental tests, we have implemented the CMA-ES algorithm to find optimal values for actuators' gaits, i.e., $\beta_i,\ \alpha_i,\ f_i$, and ϕ (figure 3C). These parameters control the search behavior of the algorithm including the parameters listed in table 1. We have tuned the parameters empirically based on experiments and observations so that the CME-AS would find optimal solutions in acceptable time and accuracy ranges. At each iteration, the suggested solutions by the CMA-ES algorithm can appear out of the feasible range of variables restricted by the mechanical constraints and limitations of the servo motors. Hence, we have defined a penalty function in order to exclude non-feasible solutions. The penalty function gradually confines the large search space to the feasible solution space of the problem. Consequently, the number of suggested non-feasible solutions decreases as the number of iterations increases.

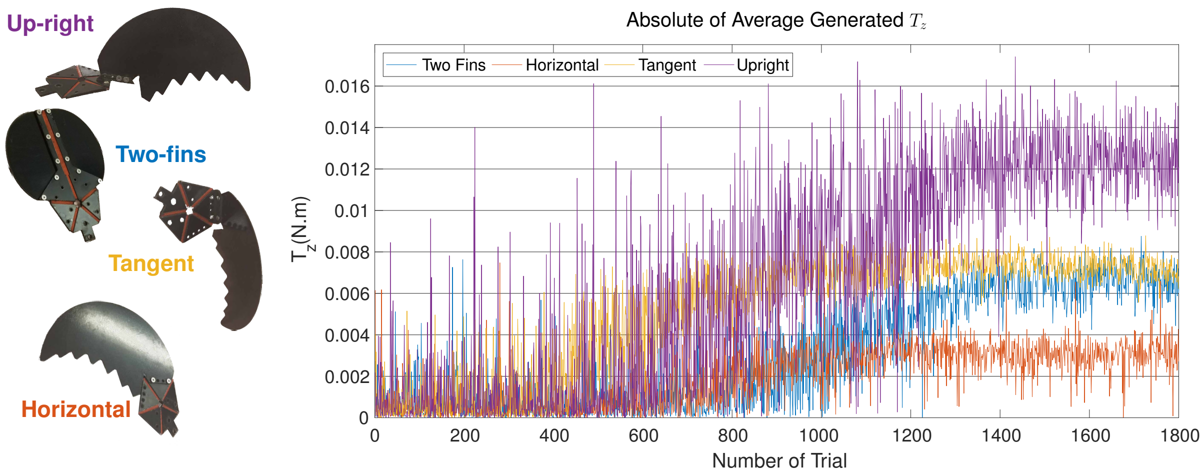

Figure 4: **Pectoral fins' attachment selection.** Value of goal function for CMA-ES training trials when UR5 is fixed (simulating still water) for different attachments.

Even a state-of-the-art algorithm like CMA-ES faces difficulty in non-ideal test environments where high disturbances may reduce system repeatability. As explained in the 'Swimming Forward' Section, in our non-ideal training environment, CMA-ES has failed to converge in a reasonable time for a free search within the 17-dimensional space. Hence, we have been obliged to define relationships to decrease the number of free gait parameters. The maximum dimension of the parameter space which we have successfully found optimal values is 7.

3.4. Selection of pectoral fin attachment

We leverage the online optimization in finding the pectoral fins attachment that enhances the turning of the robotic fish. The proposed mechanism for the pectoral fin is a 2-DOF spherical mechanism capable of creating rotation about two axes simultaneously within a finite circular workspace. The fin's attachment to the mechanism to the 5-bar mechanism is important because it impacts the fin's range of motion within that workspace. Hence, three different attachments for the spherical mechanism have been designed, built, and tested. In addition, a two-bodied fin design has been investigated. CMA-ES has been used to train each fin design for maximizing turning torque, and the best fin design has been selected based on the result obtained. Figure 4 illustrates the different fin designs, as well as the results of CMA-ES training for maximizing the turning torque generated by pectoral fins' propulsion. Figure S1 shows the torque generated by the highest performing gait as well as the convergence plots of all gait parameters throughout the CMA-ES training.

4. Results

FIRE can achieve swimming speed of 0.385 m/s (0.71 body length per second) using its caudal fin and can perform pure rotation by utilizing its pectoral fins. The turning speed in this rotation is 15.68 deg/s. To the knowledge of the authors, the proposed robotic fish is the first robotic fish to perform pure rotation using pectoral fins, with a ration radius close to zero. The obtained rotation rate using pectoral fins, though not as fast as multi-bodied tail robotic fish [12, 13] (30 50 deg/s), is comparable with other robotic fish [50] (12.6 deg/s) and [29] (7.5 deg/s). FIRE's forward swimming speed is competitive to most other state-of-art robotic fish, e.g. [2] (0.51 body length per second) and [50] (0.37 body length per second), with exception to Tunabot's 4 body lengths per second [1]. This performance is made possible via innovations in the design of the robot as well as the use of machine learning to identify good gaits, as described below.

4.1. Turning

As illustrated in figure 1B, FIRE's turning radius is important for improving maneuverability in close quarters. This is supported by literature that demonstrated how a caudal fin alone is insufficient to reduce a robot's turning radius for maneuvering in tight environments [2, 9, 51]. Using its pectoral fins, FIRE can now perform a 360-degree turn with a near-zero turning radius. Figure 2B illustrates the mechanism underlying responsible for producing the pectoral fin's motion. This mechanism's workspace and a sample time-lapse of its motion are shown in figures 2C and D, respectively.

To train the robotic fish for sharp turns, we have carried out a study to maximize the amount of turning torque generated by the pectoral fin's propulsion. Turning performance has also been used as the selection criterion for selecting the fins' optimal attachment (for more details refer to material and methods section).

FIRE achieves its best turning performance using both pectoral fins in conjunction with each other. We considered two different cases in our search for the best gait parameters. In the case of still water, the UR5 is kept stationary; in the second case, it is moved along a straight path at 0.1 m/s to simulate current. In both cases, the test is repeated three times for each set of parameters.

In presence of perturbation, our training algorithm fails to converge in a reasonable time when we try to search through the fourteen dimensional space of the pectoral fins' parameters. Hence, FIRE's pectoral fins are parameterized in such a way that their motion is synchronized along an opposite path, meaning that when one is moving clockwise, the other one is moving

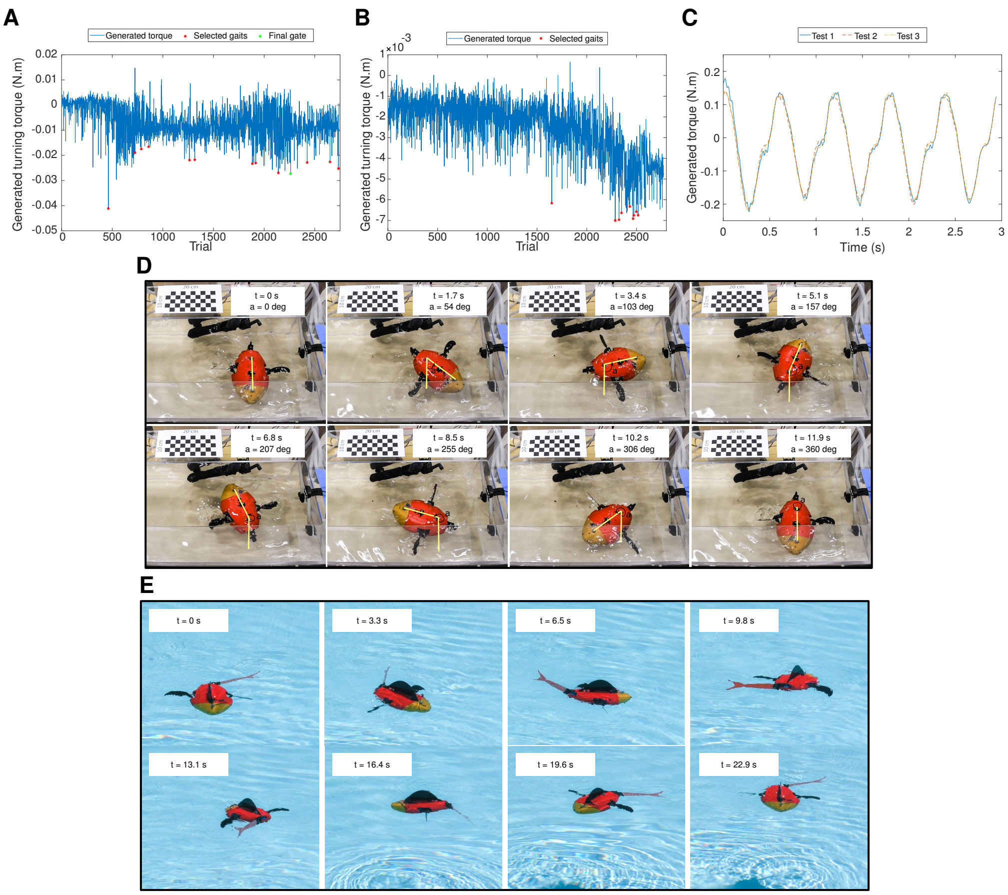

Figure 5: **FIRE's turn training. A:** Value of goal function for CMA-ES training trials when UR5 is fixed (simulating still water). **B:** Value of goal function for CMA-ES training trials when UR5 is moving with 0.1 m/s speed (simulating water with current). **C:** Turning torque generated in time for selected gait. **D:** Extracted frames of FIRE turning in the 2-feet wide tank. **E:** Extracted frames of FIRE turning in the pool.

counterclockwise. This is achieved by introducing the following relationships:

$$\alpha_1 = -\alpha_3, \quad \alpha_2 = -\alpha_4, \quad \beta_1 = -\beta_3, \quad \beta_2 = -\beta_4, \quad f_1 = f_3, \quad f_2 = f_4, \quad \phi_1 = \phi_2 \qquad (2)$$

We believe this helps magnify the turning torque generated by the fins rather than canceling them out. This assumption also reduces the gait parameter space by half from fourteen to seven.

Figures 5A and B show the turning torques generated in the CMA-ES search for the best gaits in still and moving water, respectively. Based on the peak generated torques and repeatability (marked by red star in figures 5A and B), 8 unique gaits have been selected for testing in real-world environments with an untethered fish; the best motion gait is

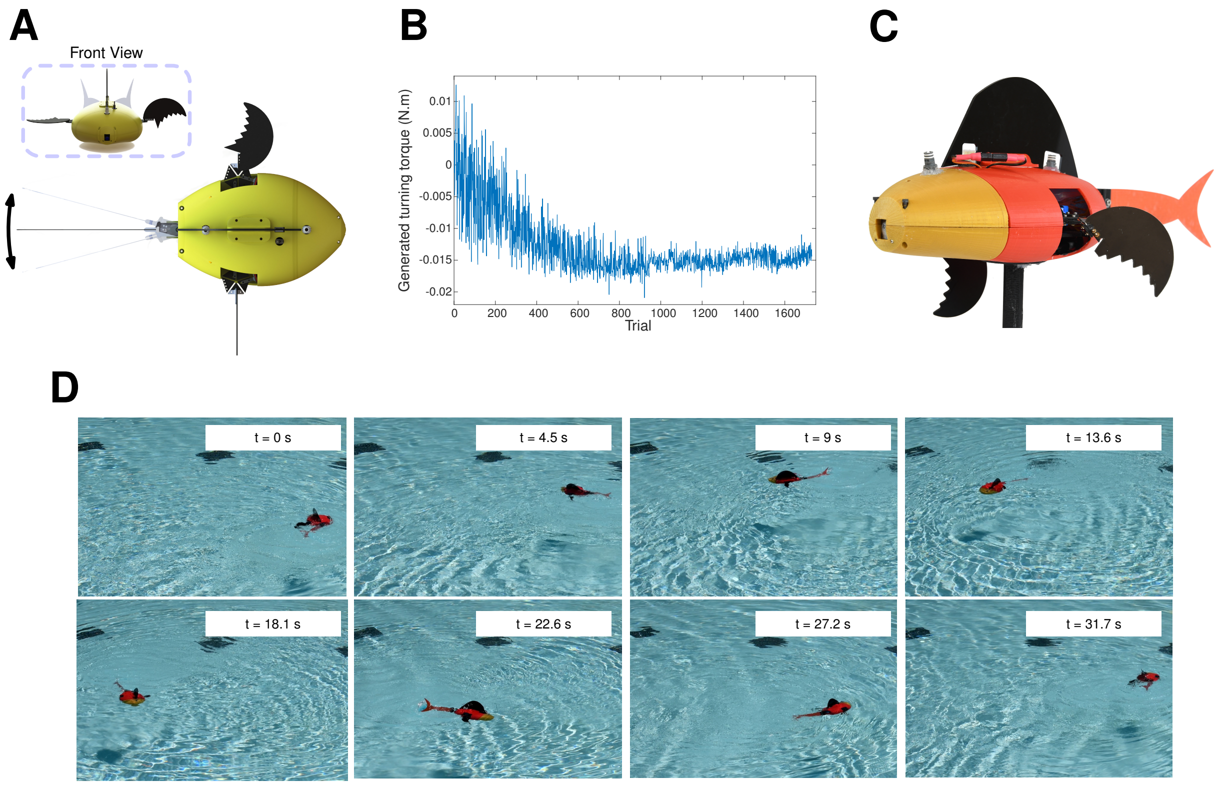

Figure 6: **FIRE's large turning radius training. A:** Concept of asymmetric drag. **B:** Value of generated turning torque for CMA-ES training trials when UR5 is moving with 0.1 m/s speed. **C:** FIRE in its turn left configuration. **D:** Extracted frames of FIRE turning left.

subsequently selected based on its performance in different environments (marked by a green star in figure 5A). Figure 5C illustrates the torque generated through time by the selected gait. Using this motion pattern, FIRE can perform a 360-degree turn with a near zero radius and the average speed of 30.25 deg/s in our two foot wide experimental lab setup (figure 5D), despite the presence of perturbations caused by waves reflected by the tank wall. It should be mentioned that the caudal fin is detached to permit FIRE to turn in the tank without hitting the walls. Figure 5E shows the performance of the same gait in a pool. While the turning speed is reduced to 15.68 deg/sec, the robot can reliably turn even when it is subjected to perturbation (Movie S1). The authors believe that the slower turning performance of FIRE can be mostly attributed to the reattached caudal and dorsal fins on the untethered robot.

For turning with larger radius, FIRE can utilize its pectoral fins in conjunction with its caudal fin. While the robot can use the gait selected above in combination with its caudal fin for larger-radius turning, we studied a more energy-efficient approach to accomplish this goal (figure 6A). In this approach, the robot's pectoral fins are fixed in different configurations in

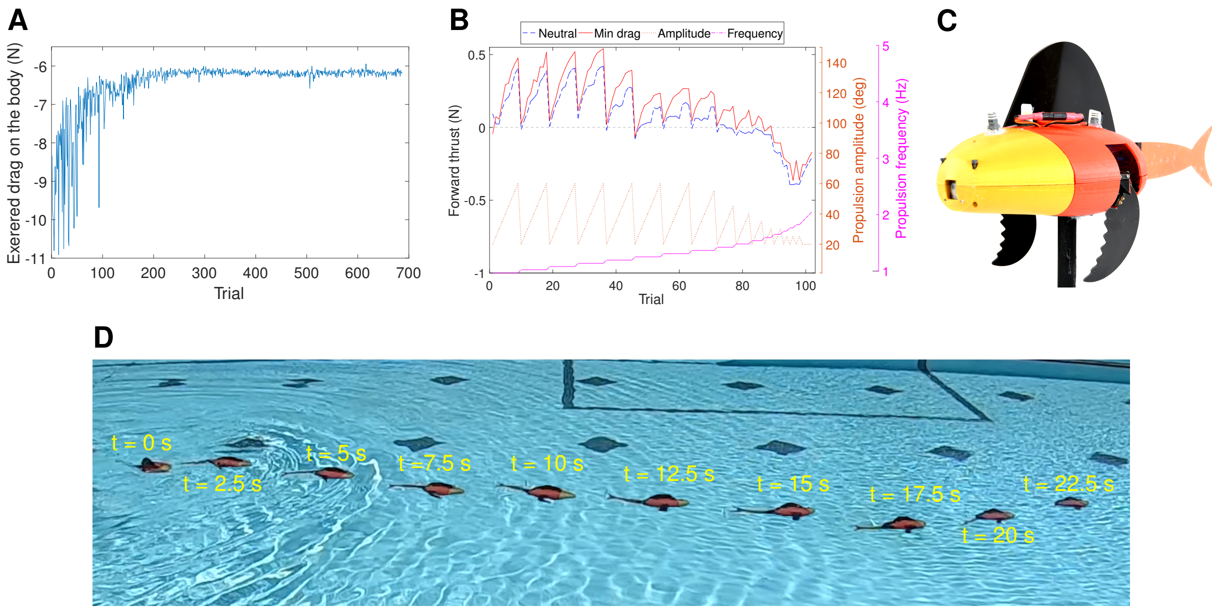

Figure 7: **FIRE's swimming forward training.** **A:** Value of goal function for CMA-ES training trials in minimizing the drag exerted on FIRE's body. **B:** Spanning gait's parameter space for caudal fin thrust generation when the UR5 is moving with 0.1 m/s speed and FIRE pectoral fins are in neutral (blue) and minimum-drag (red) configurations. Gait's amplitude and frequency are shown in orange and pink, respectively. **C:** FIRE in its minimum drag configuration. **D:** FIRE swimming forward in minimum drag configuration.

order to produce drag. This asymmetric drag on the robot's body enables FIRE to turn gradually, while saving power by avoiding continuous actuation of the pectoral fin servos. As the objective is to find the configuration that maximizes turning torque at various speeds, individual tests are repeated three times per parameter set, once at 0.1, 0.2, and 0.3 m/s each. The cost function has been defined as the summation of average turning torque across all three speeds. The selected configuration and the training procedure is shown in figure 6.

4.2. Swimming Forward

4.2.1. Body Drag Minimization The pectoral fin configuration affects the amount of drag exerted on the robotic fish. Our training algorithm has succeeded in reducing drag on the body by 40 percent across different speeds by finding the optimum pectoral fin configuration. We use the training algorithm to minimize drag by finding fixed servo positions that put both fins in an orientation that minimizes drag. Individual tests for each fin configuration are repeated three times per parameter set, once at 0.1, 0.3, and 0.6 m/s each. The obtained results in figure 7A show that the summation of the measured drag value across all speeds has been reduced from 11 N in the initial neutral configuration to 6 N in the minimum-drag configuration (figure 7C). It should be mentioned that we believe a noticeable part of the measured drag is associated with the attachments used to fix the robotic fish to the force sensor and robotic arm.

4.2.2. Forward Thrust Generation with the Caudal Fin FIRE can swim forward with a maximum speed of 0.385 m/s by relying solely on its caudal fin (Movie S1 and figure 7D). This mechanism consists of a servo motor moving a flexible, fin-shaped plastic sheet back and forth to produce thrust. Experimental results show that the tail performs best when $\alpha_5 = 60$ deg and $f_5 = 1.4$ Hz. The thrust produced by the caudal fin is controllable when $f_5 = 1.4$ Hz. Because the caudal fin is ineffective for maneuvering in tight spaces, its motion has been set to be symmetric ($\beta_5 = 0$). The three-dimensional space of function parameters ($\alpha_5, \beta_5,$ andf_5) has been spanned by measuring the average of sampled thrust produced by the caudal fin across one cycle. In this study, we search for optimal caudal fin gaits by considering the effect of water's opposing currents by commanding the UR5 arm to move at 0.1 m/s. Two different cases of pectoral fin orientations have also been considered throughout the caudal fin study. These cases are neutral and minimum-drag orientations of the pectoral fins. Figure 7C illustrates the value of thrust produced by caudal fin based on the gait's amplitude (orange) and frequency (pink) when FIRE pectoral fins are in neutral (blue) and minimum-drag (red) configurations. The maximum thrust produced by the caudal fin increases by almost 15 percent when the pectoral fins have been moved from their neutral to the minimum-drag configuration.

After fitting the drag and thrust generation plots, we can estimate that the caudal fin can achieve a forward velocity of 0.16 and 0.18 m/s when the pectoral fins are in their neutral and minimum-drag configurations, respectively. Considering that the robotic fish has attachments that increase drag during laboratory experiments, the swimming speed achievable by the untethered robotic fish is expected to be more than the value that has been estimated by matching the body drag and the caudal fin's thrust generation.

4.2.3. Forward Thrust with Caudal and Pectoral Fins The purpose of this next study is to improve forward thrust by utilizing the pectoral fins' propulsion. The obtained results show that in our current design and configuration, the pectoral fins are not capable of improving the thrust produced by the caudal fin. These results are compatible with observations of pectoral fins' propulsion being used in low speed swimming by Lauder et al. [7]. We have considered a number of different cases for this objective. In the initial case, we have performed an unconstrained full search. This has resulted in a gait search in the 16-dimensional parameters space (two for symmetric caudal fin propulsion and two sets of seven variables for each pectoral fin). In this test, for each set of parameters the test is repeated two times and the UR5 moving speed is 0.1 m/s. The obtained results show that the training algorithm has not converged after one hundred iterations (Fig. S3A). Considering that on average, each iteration takes a hundred minutes, the study has not been carried out for more iterations. Instead, some simplifications have been applied to help the training algorithm to converge. The caudal fin has been set to produce maximum forward thrust and the pectoral fins have been commanded in a way that they have symmetric propulsions (Fig. S3B). This is achieved by introducing following relationships:

$$\alpha_1 = \alpha_3, \quad \alpha_2 = \alpha_4, \quad \beta_1 = -\beta_3, \quad \beta_2 = -\beta_4, \quad f_1 = f_3, \quad f_2 = f_4, \quad \phi_1 = \phi_2 \tag{3}$$

For each set of parameters,the test is repeated three times while the UR5 moving speed is set to 0.1 m/s. The obtained results show that all tested gaits have values less than the thrust achievable by the caudal fin alone. Finally, another case has also been studied to evaluate the ability of the thrust generation of swimming with the pectoral fins with the caudal fin disabled. The highest performing gait is only capable of overcoming FIRE's body drag when the UR5 is commanded to move the fish at 0.1 m/s speed (Fig. S3C). This result shows that the symmetric pectoral fins' propulsion can produce only limited forward thrust in certain circumstances; the maximum speed achievable is around 0.1 m/s.

5. Conclusion & Future Work

In this paper, we have introduced a robotic fish that can utilize complex gait patterns via two 2-DOF pectoral fins and one caudal fin to swim in extreme environments. This is accomplished with a new two degree-of-freedom pectoral fin mechanism, whose parallel architecture permits all actuators to be integrated within the body of the fish, maintaining a more bio-inspired and lightweight fin design as well as a more streamlined body. We have carried out a comprehensive series of gait selection studies across all five degrees of freedom via a novel experimental setup design that uses a robotic arm to simulate water current. The six-dimensional set of forces and torques generated by the fins' motion has been used as the criteria for evaluating locomotion performance across a number of different goals. By parameterizing actuator motion as a set of sinusoidal functions, a thorough search has been performed using an on-line evolution strategy to find the best sets of propulsion parameters for different maneuvering objectives.

In addition to the platform design and gait selection, we have trained FIRE for use in extreme environments. To do so, we have trained the fish in a non-ideal lab setup and then we have followed up the training by evaluating the top-performing gaits in different real-world environment. Finally, we have selected the final gait that shows high repeatability in its performance. We believe that this method has advantage over performing the whole training in real-world environment, because it avoids extra complexity caused by high perturbation in real-world environment. In contrast to previous fish-inspired robotic platforms, the approach proposed in this paper can be used to train robotic fish for extreme environments in a compact and efficient lab setup. This method also avoids the extra cost and labor associated with setting up and running all experiments in a less accessible and more extreme outdoor environment. In-lab training cannot guarantee good performance in the real-world on its own. Thus, the proposed training workflow pairs the advantages of using machine learning in a non-ideal lab setup with real-world validation to find gaits that work well in a variety of environments that feature disturbances, currents, and reflected waves.

While this training approach has been effective, some challenges should be addressed. First, due to uncertainties caused by the non-ideal testing environment, data is not always repeatable. To address this we have repeated the 10 s tests more than one time for each set of gait parameters. To improve repeatability we also let the water settle between subsequent trials to minimize the effect of vortices produced by previous trials. Both of these factors increase the total run time and result in relatively long training procedured that can take a day for parameter sets with a low number of dimensions (in the range of one to three) and a week for parameter sets with a high number of dimensions (in the range of seven to ten). Another consideration is that the training failed to converge within an acceptable time for cases that have parameter sets with more than ten variables. This has been addressed in current work by introducing constraining relations between gait's parameters to reduce the size of parameters' space. Currently, these relationships are manually established; future work should use experimental design techniques in conjunction with machine learning to automate this process.

Although pursuing this data-driven approach in the presence of disturbances is challenging, this study shows that modern training algorithms such as CMA-ES are capable of finding sub-optimal gait parameters for robots in non-ideal environments, as long as they are used in combination with external validation such as that provided by our workflow, as well as by applying constraints crafted to limit the dimensionality of the search.

Despite the above limitations, the advantages of this training workflow, achieved by combining the evolution strategy training with our unique experimental setup, have provided us with the opportunity to explore a variety of different body shapes and scales as well as different fin mechanisms and attachment strategies. In contrast with prior work, using a robotic arm instead of a water tunnel to obtain force measurements at different velocities not only keeps the experimental setup more compact, but facilitates training in a more extreme environment with higher perturbation which intentionally injects noise into the training, resulting in more robust gaits.

In order to further automate the optimization of gaits against new trajectory/force goals, on-board sensors like IMUs and GPS units will need to be integrated into our learning processes; this will allow learning both in the lab and in the real world. Completely understanding the effect of each gait parameter on the forces, torques, and velocities generated by the fins requires further and more in-depth study that utilizes on-board sensors, more-efficient sampling techniques, and even more optimized learning techniques, and could lead to online learning strategies within the targeted environment. Other planned future work includes in-depth study on the inter-influence of caudal and pectoral fins' propulsion and an active buoyancy control system that will be added to the robotic fish to assist the robot to maintain contact with canal surfaces across a variety of depths, in order to complete tasks like cleaning, maintenance, and inspection. Future work also includes the control of a swarm of FIREs to accomplish common tasks such as cutting vegetation and scrubbing canal walls. We believe that the collision-free control of a swarm of FIREs would be possible due to the high maneuverability of the robot and its slow dynamics.

Appendix .1. FIRE's Bio-inspiration

As mentioned in the paper, we have been inspired by the flattened body plan of suckermouth catfish (Plecostomus) in the design of FIRE. Despite the space constraints caused by servos, swim bladders and electronics, we have designed FIRE's dimensions to be as close as possible to the fineness ratio (total length/ maximum height = 6.7-9.0) and flattening ratio (maximum body length/maximum height = 0.9-2.0) of the Hypostomus plecostomus fish reported in [52]. Our robotic fish has a fineness and flattening ratios of 4.27 and 2.3, respectively.

Another feature of suckermouth catfish pectoral fins that aligns with our goal of interacting with environment is their role in performing station-holding. Their body shape has enabled them to maintain position in high currents (known as station-holding); this is a function of the fish's body's drag, lift, effective mass and frictional forces [53, 54]. In suckermouth catfish, pectoral fins have a large toothed spine and are also used to hook the fish to the substrate and increase friction for station-holding [54, 55]. According to the study conducted in [54], performing friction-enhancing behaviors via their large pectoral fin spines and odontodes enable these fish to increase their critical current speed (maximum current speed at which a benthic fish is able to hold station without active swimming [56]) by more than eleven times. Getting inspired by multi-functionality of this fish pectoral fin, we believe that a passive or 1-DOF pectoral fin mechanism cannot contribute to reaching our goals. Hence, we have proposed a 2-DOF mechanism for each pectoral fin to provide the opportunities for performing more complex tasks using pectoral fins. The pectoral fins are designed so their neutral position mimics the shape of the sucker-mouth catfish fins in a passive state.

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