Enhancing a Model-Free Adaptive Controller through Evolutionary Computation

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ABSTRACT

Many robotic systems experience fluctuating dynamics during their lifetime. Variations can be attributed in part to material degradation and decay of mechanical hardware. One approach to mitigating these problems is to utilize an adaptive controller. For example, in model-free adaptive control (MFAC) a controller learns how to drive a system by continually updating link weights of an artificial neural network (ANN). However, determining the optimal control parameters for MFAC, including the structure of the underlying ANN, is a challenging process. In this paper we investigate how to enhance the online adaptability of MFAC-based systems through computational evolution. We apply the proposed methods to a simulated robotic fish propelled by a flexible caudal fin. Results demonstrate that the robot is able to effectively respond to changing fin characteristics and varying control signals when using an evolved MFAC controller. Notably, the system is able to adapt to characteristics not encountered during evolution. The proposed technique is general and can be applied to improve the adaptability of other cyber-physical systems.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*Control theory*

Keywords

adaptive control; model-free control; robotic fish; flexible materials; differential evolution

1. INTRODUCTION

Increasingly, robots are being deployed in complex and uncertain environments, where reaction and physical agility are essential to the completion of tasks. The adaptability and robustness exhibited by natural organisms has led to many *bio-inspired* approaches to robot design. For example, integration of soft and/or flexible materials into the morphology of a robot can partially compensate for actuation capabilities that are primitive relative to those of biological organisms [10]. Examples include the "whipping" action of a flexible fin on a robotic fish [3], shock absorption by flexible joints on a legged robot [19], and thrust generation by flexible wings on a robotic flying insect [23]. However, integrating flexible materials into a robot poses numerous challenges to controlling the system, since the flexibility of a structure affects the resulting forces and torques experienced during interactions with the environment [8]. Moreover, the properties of such components are likely to change over time due to degradation of materials and changing environmental conditions such as temperature. To produce effective locomotion, on-board controllers must account for these uncertainties.

One promising approach is *model-free* adaptive control (MFAC) [2, 20], intended for "gray box" situations where only partial, and possibly inaccurate, information is known. Like traditional adaptive control [6], this method attempts to minimize the error between desired and actual outcomes. However, instead of requiring a precise model of the system, an MFAC controller *learns* how to control a device by continually updating the link weights of an artificial neural network (ANN). Moreover, by saving recent error signals and using them as additional inputs to the ANN, MFAC controllers take advantage of state information, or so-called neural network memory. Although this is a general purpose control paradigm, the values of several parameters, as well as the structure of the ANN, need to be specified *a priori*, potentially limiting adaptability of the system. This raises the following questions. Is it possible to optimize an MFAC controller in order to enhance adaptability after deployment? And how can this be done such that the controller can account for changes in the robot morphology?

In this study we investigate the coupling of evolutionary computation with model-free adaptive control. Specifically, the differential evolution (DE) algorithm [14] is used to find *good* MFAC controller parameters that enable a robot to adapt during its lifetime to changes such as mechanical wear and material degradation. We apply this method to a simulated robotic fish that swims by means of a flexible caudal fin; an example of a target robot is shown in Figure 1. Equipping a robotic fish with a flexible caudal fin has been shown to improve efficiency with respect to thrust and power [3, 12]. However, the increase in performance introduces difficulty in controlling the system, particularly in a complex and highly nonlinear aquatic environment. Here, the ob-

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Figure 1: A prototype 3D-printed robotic fish with a flexible caudal fin.

jective for DE is to find MFAC parameters that enable the system to closely follow a desired reference signal (e.g., a desired swimming speed) while adapting to physical changes to the robotic fish caudal fin (e.g., changing fin flexibility).

The results of this initial study are promising. Compared to an MFAC controller with *typical* parameters, evolved solutions are better able to match desired reference speeds while also adapting to changes in fin characteristics. In addition, we view the pairing of adaptive control with evolutionary computation (EC) as mutually beneficial. First, EC techniques aid in finding effective control parameters, and second, the use of on-board adaptive control will help to address the reality gap [7]. Specifically, an adaptive controller should allow a robotic system to better handle disparities between simulation and reality, namely, unmodeled or poorly modeled dynamics. In this work, evolutionary optimization takes place in simulation during development in order to enhance the adaptability of the system after deployment. Our ongoing work applies this method to physical robots.

2. BACKGROUND AND RELATED WORK

Robotic Fish.

As an emerging class of embedded computing systems, robotic fish are anticipated to play an important role in environmental monitoring [15], inspection of underwater structures [5], and tracking of hazardous wastes and oil spills [22]. Similar to live fish, robotic fish accomplish swimming by deforming their bodies or fin-like appendages. This form of locomotion offers certain key advantages relative to traditional propeller-driven underwater vehicles. First, robotic fish are potentially more maneuverable, which is critical when operating in cluttered underwater environments [15]. Second, since robotic fish produce very little noise and exhibit wake signatures similar to live fish, they are less intrusive to aquatic ecosystems and offer stealth in security-related applications. Finally, with fin/body motions operating at relatively low frequencies (typically a few Hz), these systems are less likely to harm aquatic animals or become jammed with foreign objects.

Autonomy and adaptation are particularly important in aquatic environments, where human oversight is often limited, if not impossible. However, while studies of robotic fish have produced many advances over the past two decades [18, 1, 9, 15], robotic fish still do not approach their biological counterparts in terms of agility or robustness. Integrating flexible materials as fins, or as entire bodies, is one approach to improving the performance of robotic fish [16, 8]. For example, Clark et al. [3] demonstrated how a genetic algorithm can be utilized to optimize both morphological characteristics and control patterns. However, an equally important issue is how the system can adapt to changes that occur *after* deployment.

Adaptive Control.

Adaptive control is a well-established field of study for dealing with uncertainty in cyber-physical systems [6]. For example, in model reference adaptive control (MRAC), a reference model defines the desired response of the system and control laws are designed such that the controlled system is forced to behave as this reference model. However, reliance on a model of the target system makes it difficult to accommodate unexpected conditions for which the underlying reference model does not apply. In addition, the complexity associated with many physical systems, such as robots with flexible components, often renders the design of a model-based controller intractable or inconvenient.

Hou and Huang [4] first proposed the idea of *model-free* adaptive control (MFAC), based on the concept of a pseudo-partial-derivative and reliance on only system inputs and outputs. The MFAC approach we use in this study, proposed by Cheng [2], combines a traditional proportional controller with an adaptive ANN, as shown in Figure 2. As an input, the ANN receives a continuous error signal e, calculated as the difference between a desired reference input and the actual state of the robot (see Figure 3). The error signal is discretized at a sampling rate T_s, and then normalized between -1 and 1 using an error bound e_b. This normalized, discretized error signal, denoted E, is passed to the first input neuron, I_1, and then propagated to each subsequent input neuron at successive discrete sampling times. This process is repeated such that the N input neurons store the N most recent error signals E. By storing these values and using them as inputs to the ANN, MFAC controllers take advantage of state information. Additionally, at each sampling time, the input neuron values ($E_1..E_N$) are fed forward to the ANN hidden neurons ($H_1..H_N$) which in turn feed their values to the output neuron (V). The final output of the controller, u, is the sum of the value from a single output neuron and the current error signal, amplified by the controller gain K_c. Adding the current error signal to the network output improves the responsiveness of the controller. Specifically, any change in error will results in an immediate change in the controller's output. Hidden and output neurons are activated with a sigmoidal activation function.

The weights of links connecting the input layer to the hidden layer (w_{ij}) and from the hidden layer to the output neuron (h_j) are updated at each sample time. Learning rules were derived by minimizing the error signal [2]; specifically, the partial derivative of an objective function, based on the error signal, is taken with respect to the link weights. Formally, these rules are described by Equations 1 and 2:

$$\Delta w_{ij}(n) = \eta K_c e(n) q_j(n)(1 - q_j(n)) E_i(n) \sum_{k=1}^{N} h_k(n), \quad (1)$$

$$\Delta h_j(n) = \eta K_c e(n) q_j(n), \quad (2)$$

where (n) denotes the sample time and q_j refers the output of the jth hidden neuron. The number of recent error signals, N, as well as the rate at which link weights are updated (called the adaptive learning rate, η), are configurable.

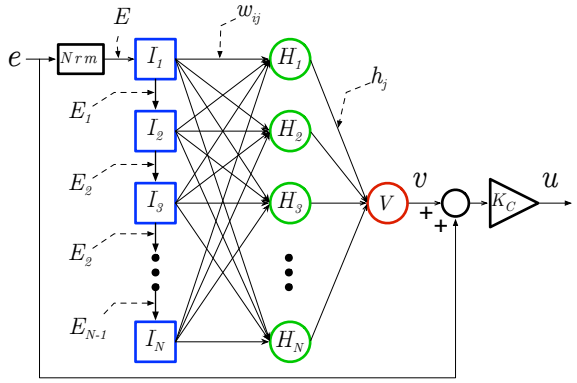


Figure 2: A graphical representation of the MFAC ANN. A continuous time error signal e is first normalized (Nrm block) and then propagated through the input neurons I_i. The ANN is then activated as a feed-forward network to produce an output v. The final controller output u is an amplified summation of v and e.

The magnitude of an MFAC controller output is adjustable through the controller gain value K_c.

Determining the optimal values of the MFAC parameters is challenging and depends on the application domain. In this study, we address this challenge with evolutionary computation. Specifically, we use the differential evolution (DE) algorithm [14] to optimize MFAC parameters (T_s, e_b, N, K_c, and η); the MFAC controllers govern a (simulated) robotic fish, which can have varying fin characteristics (i.e., fin length and fin flexibility). It is the job of an MFAC controller to adapt to these variations, which are meant to mimic changes in the caudal fin material that occur after deployment, in order to realize effective locomotion.

Before continuing, it is perhaps useful to distinguish the adaptive control process discussed in this paper from other forms of adaptive control. Specifically, a well-known method for realizing adaptability in autonomous robots is to introduce synaptic plasticity in ANNs. So-called *plastic* ANNs are able to strengthen or weaken their synapses by following a set of learning rules [17]. However, the objective for plastic ANNs is fundamentally different from that of the adaptive controllers employed in this paper. Specifically, plastic ANNs are meant to learn a new *behavior*, whereas the adaptive controller is regulating a desired control signal. For example, a plastic ANN may be used to dynamically change a swimming gait while an MFAC controller would be used to *maintain* a specific swimming speed.

3. METHODOLOGY

MFAC for Robotic Fish.

Figure 3 shows a block diagram of the MFAC controller with the robotic fish. The input to the entire system is a reference signal r, which can be any physical signal relating to the robotic fish. For this study, r refers to a *desired* speed, and the output of the robotic fish y is the *actual* (measured) speed. For physical experiments, speed can be measured by filtering and integrating accelerometer data. Generally, reference signals are generated by a higher-level module.

The controller's objective is to produce a control signal u such that y closely tracks r. That is, an effective controller

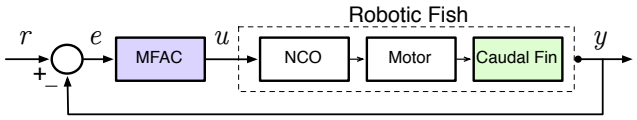


Figure 3: A block diagram of the MFAC controller and the robotic fish. Signals r and y denote the reference and measured speeds, respectively, e is the difference between reference and measured speeds, and u is the controller output.

will force the robotic fish to closely match the desired speed, and have little error e between y and r. For the robotic fish, u is a frequency of oscillation for the caudal fin motor, and a numerically controlled oscillator (NCO) generates a sinusoidal pattern at the given frequency. For this study, we have fixed the sinusoid's amplitude to 20°.

The motivating problem for this study is how to specify the MFAC parameters in such a way that they allow the controller to adapt to variations in caudal fin behavior. As a robotic fish's caudal fin undergoes regular wear and degradation it will begin to respond differently to motor commands, particularly if the fin is fabricated from flexible materials. Consequently, a static, non-adaptive feedback controller will begin to *detune*, leading to deteriorated performance. Additionally, an MFAC controller should be better able to handle noisy accelerometer data, although we do not consider noisy measurements in our simulations.

MFAC parameters are typically set based on expert knowledge. For example, the robotic fish that this study is based on has a maximum tail frequency of roughly 3.5 Hz. Cheng et al. [2] recommend for the sampling rate to be less than one-third of the period of the controlled system, or roughly 0.1 seconds for the robotic fish. The error bound used for normalization e_b can be set to near the maximum speed at which the robotic fish is expected to travel (i.e., 15 cm/s for the modeled robotic fish). A good starting point for the number of input and hidden neurons N is 3, as the ANN can interpret inputs as the current error and its first and second derivatives. This setup would roughly correspond to a PID algorithm, a widely used general-purpose feedback controller. Typical initial values for the gain K_c and the learning rate η are 1.0 and 0.8, respectively. In Section 4, we compare the performance of an MFAC controller implemented with these values to that of one with evolved values.

Simulation dynamics.

Simulation of the robotic fish is conducted in Simulink [13], enabling a straightforward translation of dynamic equations (described below) into simulation. A critical aspect of the simulation is modeling of the flexible caudal fin dynamics. The model used in this study, developed by Wang et al. [21], has proven to be both accurate and computationally efficient. Figure 4 depicts the modeled hydrodynamics. Wang's model assumes that all motions are constrained to a two-dimensional plane. Flexibility in the caudal fin is modeled as multiple rigid segments connected by springs and dampers. The spring constant between two consecutive segments determines how stiff or flexible the caudal fin behaves. The force acting on each fin segment f_i can be calculated independently, and the resulting thrust force F_T is simply a summation of all segment forces, including an additional force that acts at the tip of the final segment f_L.

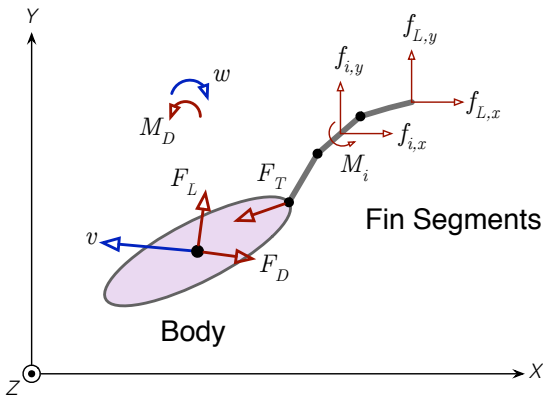


Figure 4: Graphical representation of the simulated hydrodynamics. Linear velocity v and angular velocity w are the result of thrust force F_T, drag force F_D, lift force F_L, and drag moment M_D. F_T is calculated as the sum of all forces acting on the fin segments.

The robotic fish prototype upon which this simulation is based (similar to that in Figure 1) is approximately 20 cm in length, including a 7.6 cm long tail fin of moderate flexibility made from a 3D-printed ABS plastic.

Differential evolution.

To enhance the adaptability of MFAC controllers we apply differential evolution (DE), a global optimization algorithm developed by Storn et al. [14]. DE was chosen because studies have shown that it will converge faster than real-valued genetic algorithms for problems similar to ours [11].

DE progresses in a fashion similar to other evolutionary algorithms. First, a population is randomly initialized. For this study, the population size is set to 50, which is the recommended value for a DE experiment with 5 evolving parameters (T_s, e_b, N, K_c, and η). Next, each individual is evaluated with a problem-specific fitness function. In this study, we employ two different fitness schemes. In the first, individuals are simulated for only one set of conditions, and fitness is assigned as the mean absolute error (MAE) (i.e., the average error between r and y). In the second, each individual is simulated under a variety of different conditions (varying caudal fin characteristics). Fitness is then assigned as the sum of the MAE for each set of conditions. Once each individual has been assigned fitness, the DE algorithm produces a new generation of individuals.

Mutation and crossover operators are where DE differs from conventional real-valued genetic algorithms. DE focuses on creating new individuals near the best member of the parent population. Each child is initialized as a linear combination of the best and at least two other randomly selected parents. During this recombination, the relative weight of the *best* parent to the random parents is referred to as the mutation factor and is configurable (0.8 in this study). The child is then crossed with the *base* parent (each parent is taken as the base in turn) using a configurable crossover rate (0.7 in this study). DE algorithm specifics, as well as a comparison with other evolutionary optimization algorithms, can be found in [11]. Using Storn's DE notation, the algorithm utilized for this study is denoted as DE/best/2/bin, where best signifies that all children are created around the previous generations best individual, 2 denotes that mutation is based on two individuals, and bin refers to a binary crossover operation.

MFAC parameters are allowed to evolve only within a certain range. The range for each parameter is listed in Table 1. These ranges are based on the typical MFAC parameters discussed earlier.

Parameter	Minimum	Maximum	Typical
T_s (s)	0.0	0.17	0.1
e_b (cm/s)	5.0	50.0	15.0
N	1	8	3
K_c	0.1	4.0	1.0
η	0.1	4.0	0.8

Table 1: Evolutionary range of MFAC parameters, as well as the typical values.

4. SINGLE-EVALUATION RESULTS

In this set of evolutionary experiments we evolve MFAC parameters under a single set of conditions. However, we first conduct a simulation of the robotic fish incorporating typical MFAC parameters (as listed in Table 1). Figure 5 shows results from this simulation. The task for the MFAC controller is to track a reference speed r (the orange, dashed line in Figure 5), which varies over time according to a predefined pattern. This reference speed, utilized during evolution and most test cases, is designed to contain periods requiring acceleration, deceleration, and sustaining a constant speed. Despite choosing parameters based on expert knowledge, the controller struggles to track (i.e., closely match) the reference speed. Ideally, in Figure 5 (and all similar figures) the solid blue line (y) would match the dashed orange line (r), and the error line (e) would remain at zero.

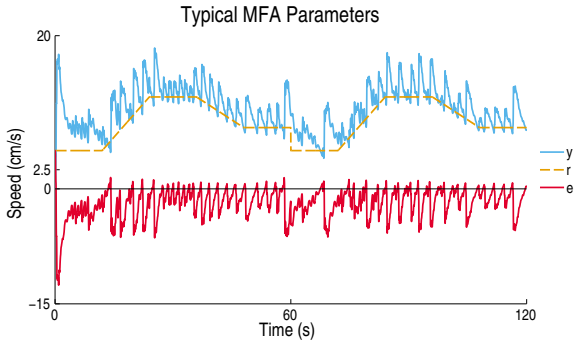


Figure 5: Results for an MFAC controller with typical parameters controlling a robotic fish. The dashed orange line denotes the reference speed r, the actual speed y of the robotic fish is the blue line, and the error e between these signals is red.

After the initial simulation using typical parameters, we conducted 20 replicate differential evolution (DE) experiments. Replicates are seeded with a unique number, and DE algorithm parameters are configured as described in Section 3. Each set of MFAC parameters (i.e., individual solutions) is evaluated under identical circumstances: it is simulated for 60 seconds with the same reference speed signal, and fitness is measured as the mean absolute error (MAE). All replicate experiments converge to similar fitness values within 150 generations.

As shown in Figure 6, solutions from the single-evaluation experiments perform the evolutionary task well (i.e., tracking the reference speed encountered during evolution for 60 seconds). However, even a slight change to this task, such as doubling the simulation to 120 seconds, causes a large change in performance. This behavior can be seen during the final 60 seconds of Figure 6, where simply repeating the reference signal results in poorer tracking and increased error. This experiment demonstrates that evolved solutions are incapable of adapting to new conditions while maintaining the same level of performance. More specifically, the evolved parameters appear to be *overfit*. The best solutions only work for the conditions encountered during evolution.

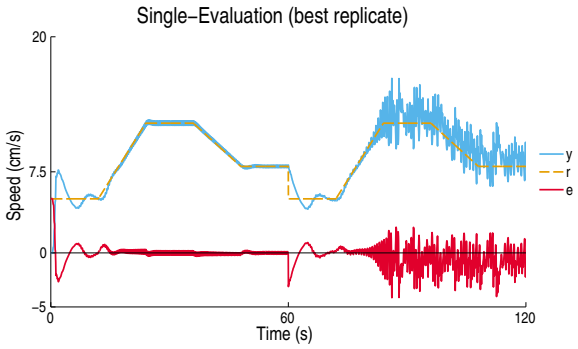


Figure 6: Results for the overall best (across all replicate experiments) single-evaluation solution simulated with default fin characteristics and the same reference signal utilized during evolution. The controller shows poor performance starting at the 80 second mark, and similar results were found in all replicate experiments.

5. MULTI-EVALUATION RESULTS

Given the results from Section 4, we conducted a second set of experiments in which fitness of each individual is based on its performance under *multiple* different conditions. The settings for these simulations, referred to as the 9-evaluation experiments, are listed in Table 2. In the table, *sim1* corresponds to the conditions used in the previous experiments. For each simulation, fin flexibility is set to: 100%, increased to 200%, or decreased to 50% of the default value. Likewise, the caudal fin length is set to: 100%, lengthened to 110%, or contracted to 90% of the default value.

Name	Flexibility	Length
sim1	100%	100%
sim2	200%	100%
sim3	50%	100%
sim4	100%	110%
sim5	200%	110%
sim6	50%	110%
sim7	100%	90%
sim8	200%	90%
sim9	50%	90%

Table 2: Fin characteristics for the 9-evaluations experiment.

Evaluating individuals under a variety of conditions is intended to eliminate the tendency of evolving overfit solutions. Experiencing multiple conditions also simulates how fins may change once deployed. For example, fin dynamics can change if the fin is damaged (e.g., cut) or encumbered by environmental entities (e.g., seaweed). Fitness is calculated as the summation of the MAE from each of the 9 60-second simulations. Evolving with this fitness function is meant to add an implicit objective to the fitness function: better solutions must be more adaptable.

Figure 7 shows the best solution from 20 replicates of the 9-evaluation experiments. Here, the controller continues to closely track the reference for 120 seconds, even though evolutionary evaluations are only 60 seconds in length. Figure 8 shows that tracking is accomplished by adjusting the fin's oscillating frequency in a pattern roughly matching that of the reference signal. Although this test indicates improvement over the single-evaluation experiment, it does not address the issue of adapting to different conditions.

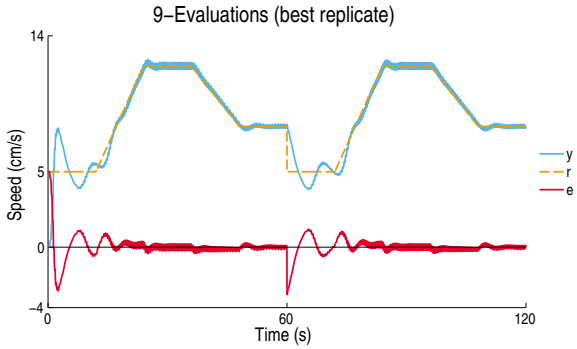


Figure 7: The overall best 9-evaluation solution evaluated on *sim1*. The MFAC controller is able to drive the robotic fish at the desired reference speed (r).

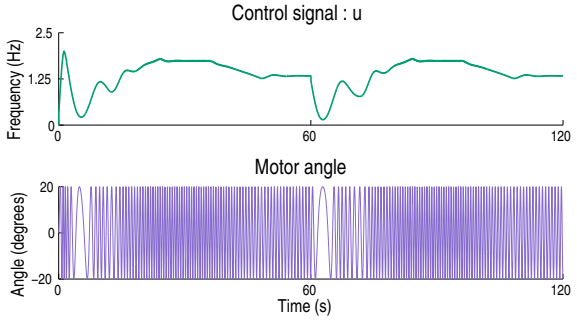
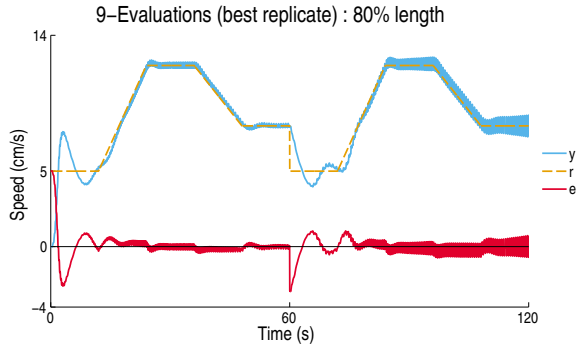


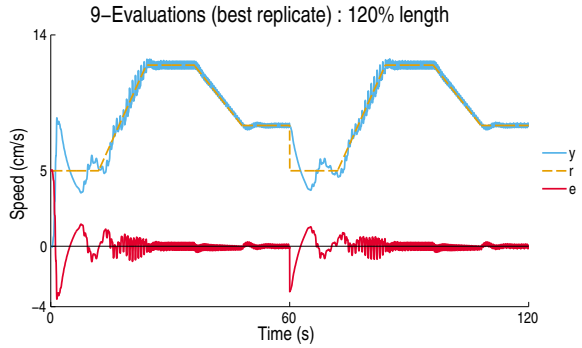
Figure 8: Control signal u and the resulting motor angle for the overall best 9-evaluation solution evaluated on *sim1*. The control signal trajectory roughly follows the reference signal.

Figure 9 depicts performance of the same solution when confronted with conditions that were *not* encountered during evolution. As shown, the controller is able to adapt to the novel fin lengths. This evolved MFAC controller should allow a robotic fish to maintain a certain level of performance even if the fin length changes during operation.

The fin can, however, reach lengths that cause the controller to lose its tracking ability. While fixing fin flexibility and the reference signal, we performed a sweep over a wide range of different fin lengths and found that the controller can maintain performance while caudal fin length is within a range of 60% to 137% of the default value. Effectively the caudal fin can be cut from 7.6 to 4.5 cm (or lengthened to



(a)



(b)

Figure 9: The overall best 9-evaluation solution tested against fin lengths that were not encountered during any of the evolutionary simulations. In (a) fin length is shortened to 80% of the default length, and in (b) fin length is lengthened to 120% of the default length. In both cases, the evolved controller is able to adapt to a novel fin length.

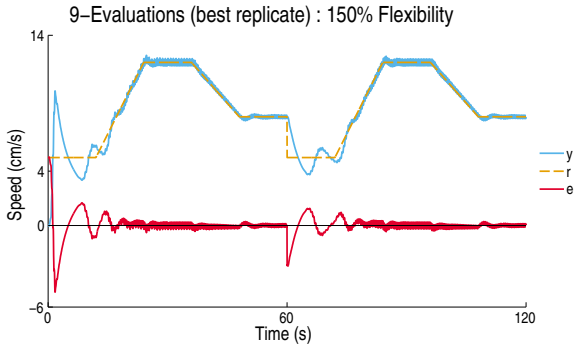


Figure 10: The overall best 9-evaluation solution evaluated with a fin that is 150% of the default fin flexibility. Evolved controllers were able to adapt to this novel value for flexibility.

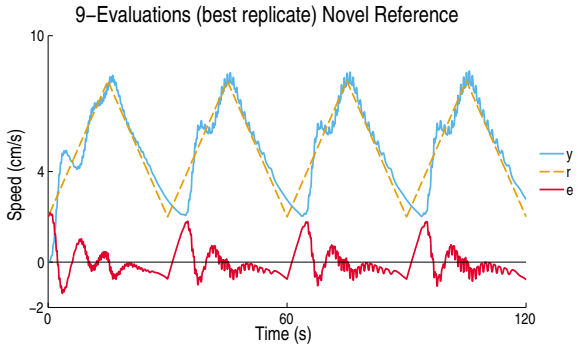


Figure 11: The overall best 9-evaluation solution simulated with default fin characteristics and a reference signal not encountered during evolution.

10.4 cm) without the controller losing its ability to drive the robotic fish at a desired speed. Values outside of this range cause a noticeable increase in the error signal.

Figure 10 shows that evolved controllers are also able to adapt to changes in fin flexibility. Similar to the fin length parameter sweep, we found upper and lower limits for fin flexibility changes. While keeping all other factors constant, the evolved MFAC controllers can maintain performance as long as flexibility remains within a range from 90% to 160% of the default value.

In addition to changes in fin characteristics, evolved controllers have the ability to adapt to different reference signals. Figure 11 demonstrates that an evolved controller is capable of tracking a novel pattern for the reference speed, in this case alternating periods of fast acceleration and deceleration. Additional test results (not shown) demonstrate that limits on the reference signal depend only on the limits of the robotic fish. Specifically, the adaptive controller will remain effective as long as the reference signal does not require speeds, accelerations, or decelerations that are impossible for the robotic fish. For example, if the reference signal changes too quickly, the robotic fish may not be physically capable of accelerating fast enough.

Figure 12 shows how the evolved controller handles simultaneous changes to both fin length and fin flexibility. For this test, fin length is set to values outside of the range encountered during all evolutionary simulations. For the test in 12(b), increasing the fin's length actually allows the evolved controller to adapt to a flexibility (80%) that would otherwise cause performance degradation. Specifically, a flexibility of 80% (of the default value) is beyond the lower limit found when flexibility was altered in isolation (i.e., the range of 90% to 160% mentioned previously). This is indicative of the complex interactions among material properties (e.g., flexibility and dimensions). Such interactions cause difficulties when designing a simple feedback controller, such as a PID controller, or a model-based controller that must account for all of the necessary dynamics. An evolved adaptive controller can automatically handle these complex interactions.

To further increase adaptability of an evolved MFAC controller (i.e., increase the range of fin characteristic variation while maintaining the same performance levels), the 9-evaluations experiments were repeated with larger variations from the default values. For instance, in *sim5* (refer to Table 2) the flexibility is set to 1000% of the default value, and length is increased to 200% of the default value. Likewise, in *sim9* flexibility is set to 10% of the default value, while length is decreased to 67% of the default value.

Although the evolved controller is generally still able to track r, the best solutions from all replicates performed worse, on all test cases, than previous solutions. Figure 13 shows an individual from the altered experiments.

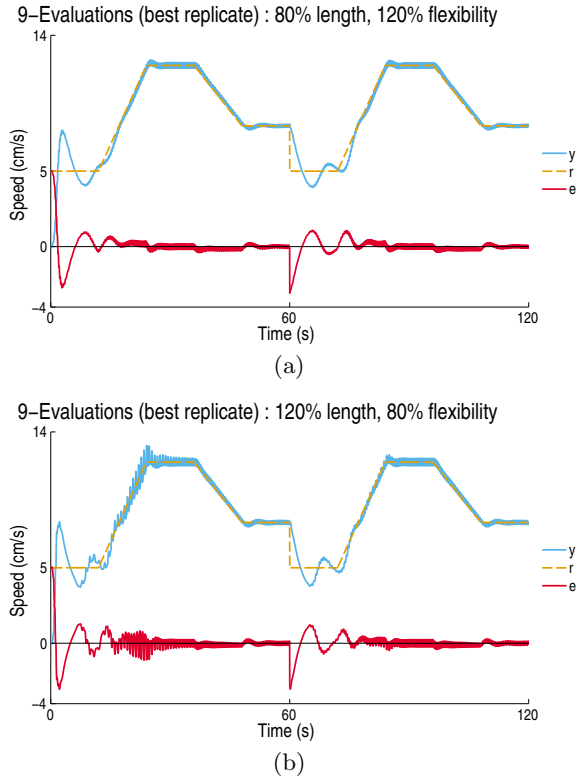


Figure 12: The overall best 9-evaluation solution tested against fin lengths and fin flexibilities that were not encountered during evolutionary simulations. In (a) fin length is shortened to 80% of the default length and the flexibility is increased to 120% of the default, and in (b) fin length is lengthened to 120% of the default length and fin flexibility is reduced to 80% of the default value.

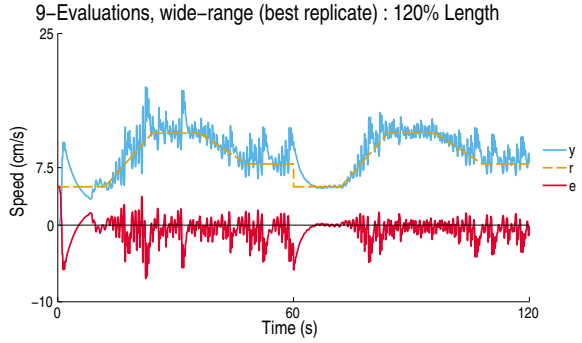


Figure 13: Performance of the best evolved solution from the altered 9-evaluations experiments tested with a fin length 120% of the default.

The primary reason for the MFAC's inability to adapt to large variations lies in how the dynamics change. Certain fin characteristics or combinations of characteristics cause the physical system to behave fundamentally differently. The basic MFAC presented in this study relies on the robotic system to be *direct-acting*. That is, as the MFAC controller output increases, the output from the controlled device must monotonically increase. Figure 14 depicts how changes to fin characteristics can alter the robotic fish's response to commands from the controller. Essentially, if fin characteristics vary beyond a certain threshold, the robotic fish may no longer behave as a direct-acting robotic system. This issue is most clearly demonstrated by the green, dotted curve (200%), which changes from direct to reverse-acting near 1.5 Hz, and then back to direct-acting near 3.5 Hz. A similar effect can be seen, to a lesser extent, for each of the curves. Even an optimized MFAC controller will be unable to cope with these highly varied dynamics.

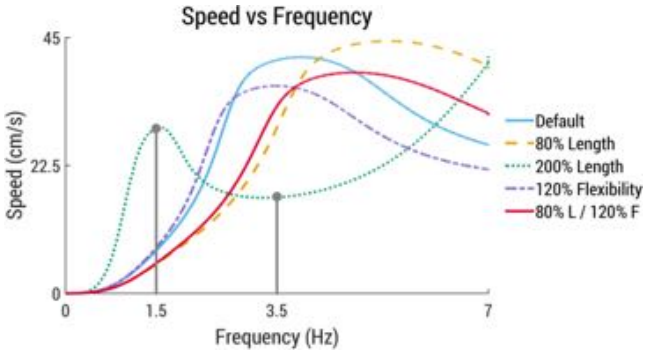


Figure 14: Speed vs. oscillating frequency for several different fin characteristics. For certain conditions increasing the frequency results in slower speeds.

6. CONCLUSION

In this study, we explored the integration of evolutionary computation and adaptive control. Specifically, we applied differential evolution to optimize the parameters of a model-free adaptive controller. The goal of evolution is to find a set of parameters that enable an MFAC controller to adapt to changes in fin characteristics (i.e., length and flexibility) and changes to the reference signal (e.g., faster/slower accelerations). Additionally, evolved MFAC controllers should be able to handle changes to the reference signal (i.e., different desired reference speeds).

Results show that evolving MFAC parameters against a single set of fin characteristics can produce a controller capable of achieving *good* fitness (i.e., specifically, low mean absolute error). However, these solutions do not produce a controller capable of adapting to changing fin characteristics. Next, the fitness function was modified to include a variety of different fin characteristics. The newly evolved controllers were tested under several different conditions, including scenarios in which the fin characteristics were outside the range experienced during evolution. This method succeeded in generating more adaptable controllers. Specifically, the best MFAC controllers were able to maintain close tracking as long as fin length remained within 60% to 137% of the default and fin flexibility remained within 90% to 160% of the default.

To explore the limits of this approach, the fitness function was again modified to include a larger variety of different characteristics. However, these experiments resulted in poorer performing controllers. Drastically varying the fin characteristics essentially creates a fundamentally different set of governing dynamics. Evolved controllers require the system to be either direct- or reverse-acting, which is not always the case when, for example, the fin is made to be too flexible; in such cases, increasing the control frequency

results in slower speeds rather than faster. Even the most fit individuals were incapable of successful adaptation when subjected to such conditions.

We note that the MFAC controllers presented in this study are designed to handle a single-input, single-output (SISO) system. However, more complex MFAC controllers have been designed to accommodate multiple inputs and multiple outputs. In the future, we plan to extend the approach presented in this study to include tracking a desired reference heading while simultaneously tracking a reference speed. Doing so will produce controllers capable of more complex behaviors that incorporate both turning and forward locomotion. Adaptive techniques may also improve an evolved solution's ability to cross the reality gap, as all unmodeled and poorly modeled dynamics will be treated as variations and accounted for during adaptation. Although this study demonstrates adaptation in the aquatic domain, the proposed technique can be applied to similarly control the speeds of terrestrial robots, and more broadly to other cyber-phsyical system.

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