Evolutionary Optimization of Robotic Fish Control and Morphology

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ABSTRACT

The nonlinear dynamics of an aquatic environment make robotic fish behavior difficult to predict and subsequently difficult to optimize. In this paper, we present a method for optimizing robotic fish propulsion through the evolution of control patterns and caudal fin flexibility. Evolved solutions are evaluated in a physics-based simulation environment. Control signals are generated with both simple sinusoids and neural oscillators. This study demonstrates how evolutionary algorithms can be utilized to handle the complex interactions among material properties, physical form, and control patterns in an aquatic environment.

Categories and Subject Descriptors

I.2.9 [**Artificial Intelligence**]: Robotics—*Autonomous vehicles,Kinematics and dynamics*

Keywords

evolutionary robotics; neural oscillator; robotic fish; morphology

1. INTRODUCTION

Designing a robotic fish is a challenging engineering endeavor. The nonlinearity of an aquatic environment and the complex interactions between morphology (i.e., physical form and material properties) and control give rise to a system that is difficult to model. However, dynamic models recently developed by Wang et al. [6] encapsulate the hydrodynamic interactions contributing to robotic fish thrust and can be incorporated into a simulation environment. These models account for different caudal fin dimensions and degrees of flexibility. Our work integrates these hydrodynamic models into an evolutionary algorithm in order to optimize robotic fish morphology and control.

A common method for controlling a robotic fish is to apply an oscillating signal to the caudal fin. With a sinusoid control signal, the resulting velocity of a robotic fish can be adjusted by varying the frequency and amplitude, and turning can be achieved by adding a constant bias (a vertical shift of the wave). While this method is simple, the more complex signals produced by neural oscillators may produce motion that more closely resembles the changing amplitude patterns of live fish. We have implemented the neural oscillator proposed by Matsuoka in [4], referred to as a Matsuoka Neural Oscillator (MNO), and compared it to sinusoidal controllers. In our experiments, evolution is responsible for optimizing both control and morphology in order to improve propulsion. Through controller-morphology evolution, the complex internal interactions between actuation and material properties can be exploited to produce a system that matches the needs of its environment.

In prior work [2], we investigated flexible caudal fins using a fixed controller. In this study, we allow evolution to optimize both the morphological characteristics of a caudal fin, as well as the control patterns governing its motion. The primary contribution of this paper is a demonstration of how an evolutionary algorithm can handle the complex interactions among material properties, physical form, and control patterns in an aquatic domain. This result is demonstrated by comparing the performance of MNOs against pure sinusoid waves in maximal velocity experiments. Additional details of this study are available in a technical report [1].

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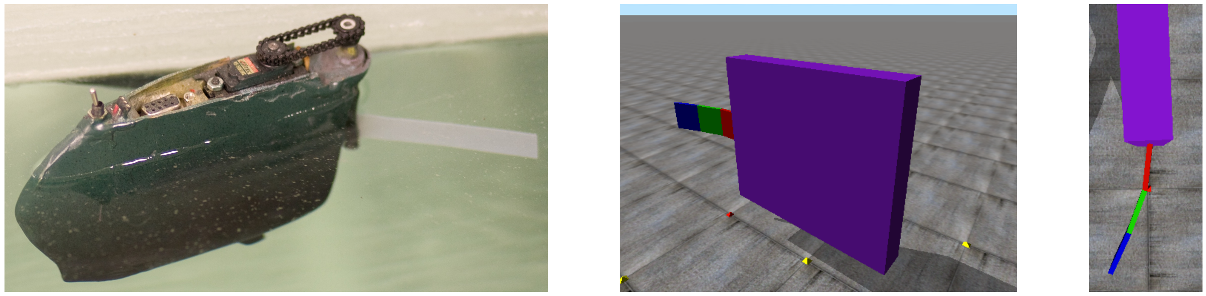
2. METHODS

Figure 1 shows the physical device and the derived simulated approximation. The only actuated component of both the physical and simulated robots is the caudal fin. On the prototype, a servo motor controls the angle between the body and fin by rotating the caudal fin around the body-fin pivot point. Likewise, the simulated fish can change the angle of a hinge between the body and fin. The hinge has minimum and maximum angles of $\pm$ 55 degrees, and a maximum absolute angular velocity of one revolution per second, roughly half the angular velocity of a typical unloaded servo motor.

To address the challenges associated with simulating flexible materials and an aquatic environment we relied on Open Dynamics Engine (ODE) [5], an open source physics package, and a dynamic model. The dynamic model, developed by Wang et al. [6], is based on Lighthill's Elongated Body Theory of Locomotion [3]. The model accounts for flexibility by segmenting the fin into multiple sections. The force acting on each fin segment can be calculated independently, and the resulting thrust force is calculated as the combination of all segment forces as well as an additional tip force acting at the posterior of the fin.

All of our evolutionary experiments were performed using a variant of the conventional genetic algorithm (GA). In general, every individual in the population encodes the controller parameters as well as the caudal fin flexibility. We start by randomly initializing the population, and then



(a) (b) (c)

Figure 1: Overview of the simulated robotic fish. (a) The robotic fish prototype at the basis of our study and utilized in model development; (b) the virtual robotic fish; and (c) the virtual flexible caudal fin composed of three rigid segments.

continue through a sequence of generations in which each individual is evaluated and stochastically reproduced based on fitness. All experiments included 200 individuals and 100 generations of evolution. The GA utilizes size 3 tournament selection for recombination, crossover, and mutation.

3. RESULTS AND DISCUSSION

The primary goal of our experiments was to explore the effectiveness of evolution as it applies to optimizing robotic fish propulsion. To determine the utility of our proposed method, we performed a series of experiments in which we compare MNOs to pure sinusoidal signals. In these experiments, the target of evolution is to reach a maximal average velocity. To ensure that initial MNO transients and starting bias do not affect the stable average velocity measurement, which is our fitness metric, all evaluations began after a 5 second start-up period; the total evaluation period is 15 seconds.

Figure 2 summarizes all of the experiments. To provide a basis for our evolution experiments we first limited evolution to the control parameters with a fixed morphology. In these experiments, MNO and sinusoid controllers had similar performance. Next, we allowed evolution to alter both control and morphological parameters. In these experiments, the average velocity was substantially higher than when only control parameters were evolved. Additionally, in these experiments we found that pure sinusoids outperformed the MNO-based controllers.

This study demonstrates that evolutionary algorithms can handle the complex interactions found among material properties, physical form, and control patterns. Our ultimate goal is to utilize evolutionary computation to help design robotic fish that are faster and more maneuverable than current systems.

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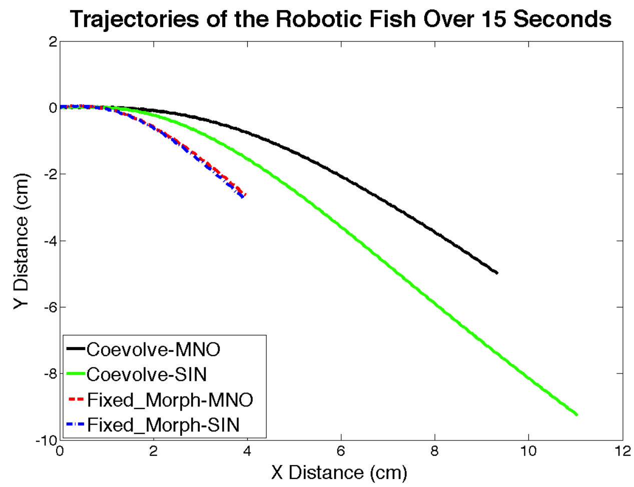

Figure 2: Paths of the best evolved solutions.

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