ROBOTIC FISH:

FLOW-RELATIVE CONTROL BEHAVIORS USING DISTRIBUTED FLOW SENSING

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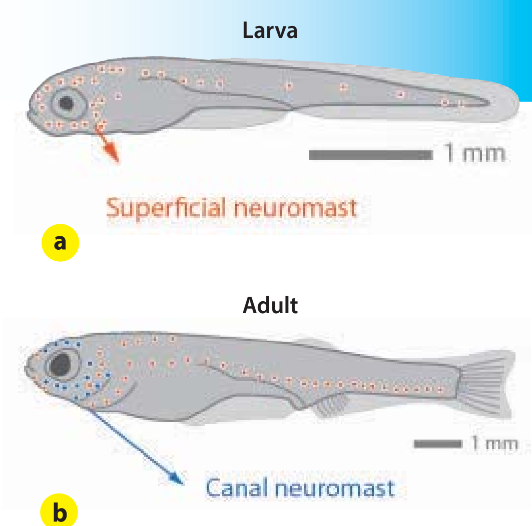
Over millions of years of evolution, fish have developed a flow-sensing system to detect the surrounding fluid motion, which consists of hundreds of receptor organs distributed on – and under – the skin [1]. Flow sensing serves an important role in swimming behaviors such as rheotaxis (orientation into or against the flow direction), station holding, predation, and schooling.

Advanced underwater vehicles that are biologically inspired attract scientific attention because of their potential for energy efficiency and maneuverability [2,3,4,5]. A flow-sensing capability enables robotic fish to navigate in unknown, murky, and cluttered environments. To demonstrate bio-inspired flow sensing and control using distributed pressure and velocity sensors, a rigid airfoil-shaped robotic fish [6,7] and a flexible, self-propelled robotic fish [8] have been developed at the University of Maryland. The robots are capable of rheotaxis, station holding, and speed control using a recursive Bayesian algorithm to assimilate measurements of the flow. A closed-loop control strategy that comprises feedback and feedforward designs has been validated in experiments.



THE LATERAL-LINE SYSTEM

The lateral line is the fish's sensory system for flow movement and vibration **(Figure 1)**. It consists of two types of sensing organs: canal neuromasts, which approximate the pressure gradient, and superficial neuromasts, which measure local flow speed [1]. A variety of artificial lateral-line systems [9,10] have been proposed for detecting flow movement, with the majority inspired by canal neuromasts due to the advantages in availability and performance of pressure sensors as compared to velocity sensors. There exists some research on flow estimation by underwater robots using artificial lateral-line systems [11,12], mostly based on empirical flow models generated from training data and/or applied to a towed rigid-body underwater robot. However, we have found very little prior work in the area of flow sensing for a flexible, self-propelled underwater robot using an analytical flow model and no prior work

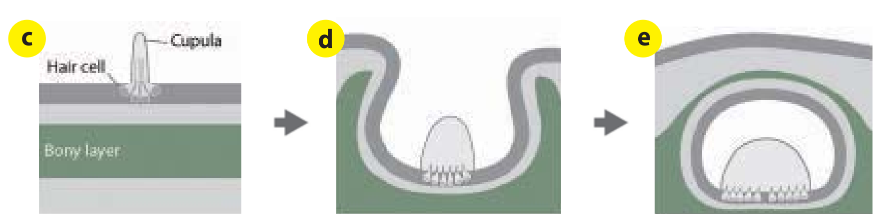


FIGURE 1 The lateral-line sensing organ in zebrafish; (a) Superficial neuromasts in larval fish; (b) canal neuromasts in adult fish; (c) structure of a superficial neuromast; (d) development of a canal neuromast; (e) structure of a canal neuromaast.

ZEBRAFISH DRAWINGS COURTESY OF MATTHEW MCHENRY, UNIVERSITY OF CALIFORNIA, IRVINE for this type of robot executing closed-loop behaviors based on an estimated flow field.

ROBOTIC-FISH DESIGN

The Collective Dynamics and Control Laboratory at the University of Maryland has constructed two robotic fish to study bio-inspired flow sensing and control of underwater vehicles. **Figure 2** shows a rigid, airfoil-shaped robotic fish made from composite polymer using a 3D printer. Mikro-Tip Catheter pressure sensors SPR-524 from Millar Instruments and ionic polymer metal composite (IPMC) sensors fabricated at Michigan State University [7,13] are embedded to measure local water pressure and velocity, respectively. The shape of the robot is a Joukowski airfoil, which is the output image of a conformal mapping of a circle [14] and is conducive to modeling the fluid analytically. This robotic fish measures 9.9 cm long, 2.2 cm wide, and 6 cm tall. A stepper motor with high-precision position control regulates its orientation and cross-stream position in a flow channel (185 L, Loligo).

The second robot is a flexible, self-propelled robotic fish **(Figure 3)** fabricated using a soft material, Ecoflex silicone rubber from Smooth-On with Shore 00-30 hardness. A mold was designed in Solidworks with the Joukowski airfoil shape and manufactured using a high-precision 3D printer; the mold holds the mixed compound of the soft material until cured. Embedded in the robot during the molding process are MEMS-based pressure sensors from Servoflo (MS5401-BM), which output analog voltage in proportion to the local pressure. The flexible robotic fish measures 20 cm long, 3.6 cm wide, and 12 cm tall. A shaft from MakerBeam was inserted at the one-quarter-point of the chord behind the leading edge to serve as the actuation-axis pivot. When rotated, the fish robot body deforms in a continuous way with the largest displacement at the trailing edge, mimicking fish swimming motion.

FLOW-SENSING ALGORITHM

Fish sense pressure differences (resp. local flow velocities) using canal (resp. superficial) neuromasts. Robotic flow sensing relies on mathematical modeling that relates pressure and velocity measurements to flow states such as the angle of attack and flow speed. Our research leverages two flow models: a quasi-steady potential-flow model [14] and an unsteady vortex-shedding model [15,16]. The quasi-steady model describes the flow past a cambered Joukowski airfoil using the relative flow speed, the angle of attack, and the camber ratio of the fish robot, which reflects the degree of the body bending. The velocity vector field is calculated from a complex potential function that depends on the three flow parameters. The vortex-shedding model captures the unsteady effect of fish flapping by introducing a point vortex into the flow field at each time step. However, the resulting increase in the system dimension leads to an unaffordable computational burden for real-time application. Thus, the quasi-steady flow model is used in the estimation algorithm and the vortex-shedding model is used only in simulation.

From the Bernoulli equation, the pressure difference between two sensors is a nonlinear function of the local flow speed at the locations of those two sensors. The nonlinearity in the measurement function led us to adopt a Bayesian filter [17] to assimilate sensor measurements for flow sensing. A Bayesian filter is a general probabilistic approach for estimating an unknown probability density function (pdf) from incoming measurements. It permits a nonlinear measurement function and non-Gaussian measurement noise. The flow-sensing measurements obtained from the robotic fish are the pressure differences between each pressure sensor pair and the local flow velocity at each IPMC sensor (when available). The estimation states may include the relative flow speed, the angle of attack, and the camber ratio, which is zero in the case of the rigid robot. The Bayesian filter recursively updates the pdf of

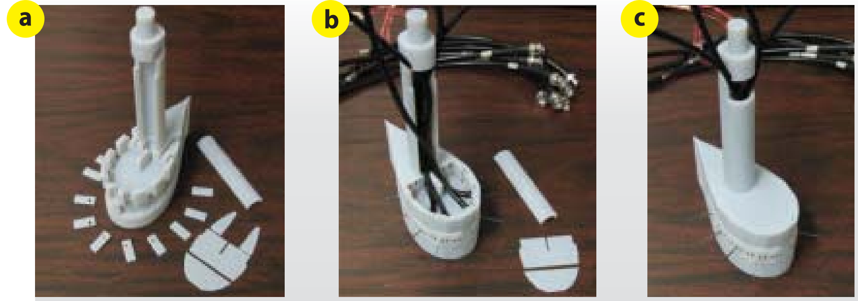


FIGURE 2 Rigid robotic-fish design with eight IPMC sensors and four pressure sensors [7]. (a) Modular 3D-printed parts; (b) sensor configuration; and (c) full assembly of robotic fish with artificial lateral line.

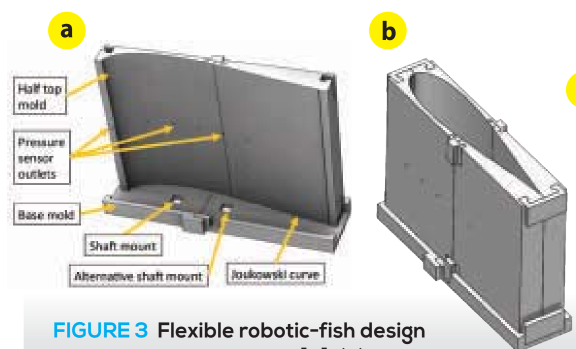


FIGURE 3 Flexible robotic-fish design with molding techniques [8]. (a) Mold interior; (b) mold assembly; and (c) the flexible robotic fish with embedded sensors.

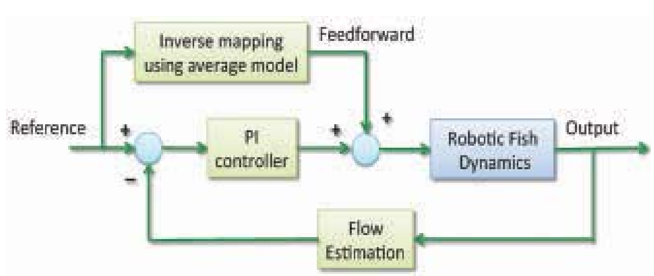
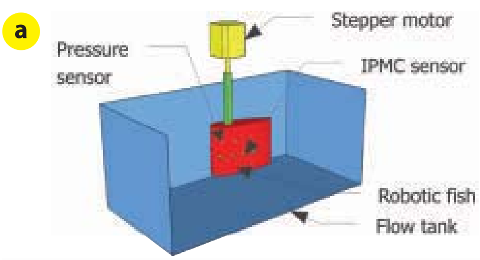


FIGURE 4 Block diagram of the closed-loop control system, combining feedforward and feedback control.

the estimated states that describe the flow field in order to provide real-time flow parameter estimates to the controller.

FLOW-RELATIVE CONTROL

A closed-loop control strategy that comprises feedforward and feedback designs achieves flow-relative behavior in the flexible robotic fish. **Figure 4** illustrates the control design in block-diagram form. The objective is to drive various states of the robotic fish to track desired reference signals by regulating the flapping amplitude and frequency. The feedforward controller is the inverse mapping of the dynamic model [18] of the robotic fish averaged over a single flapping period. The feedback controller includes proportional and integral terms based on information from the flow estimate. The feedforward term accelerates the convergence of the tracking control, and the feedback term improves the tracking performance by reducing the steady-state error.



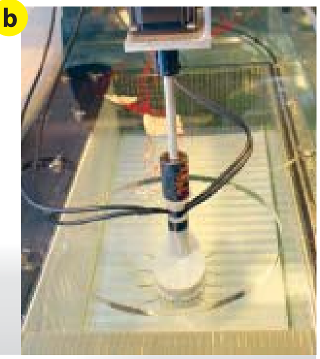


FIGURE 5 Rheotaxis experiment using the rigid airfoil-shaped robotic fish. (a) Schematic of the testbed; (b) experiment snapshot.

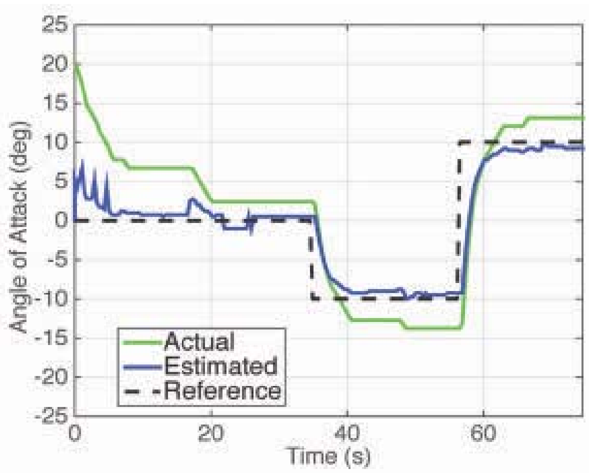


FIGURE 6 Trajectories of actual (solid green), estimated (solid blue), and reference (dashed black) angle of attack in rheotaxis experiment [7].

RHEOTAXIS CONTROL

Rheotaxis is a form of taxis observed in fish in which they generally orient into (or against) an oncoming current. The rheotaxis behavior requires sensing the flow direction. The rigid airfoil-shaped robotic fish **(Figure 2)** experimentally demonstrated rheotaxis behavior using a 185 L Loligo flow tank that generates approximately laminar flow **(Figure 5)**. A real-time, recursive Bayesian filter assimilated the pressure and IPMC sensor data in order to estimate the flow speed and angle of attack. A servomotor used these estimated quantities to regulate the orientation of the robotic fish by tracking the desired angle of attack, e.g., zero degrees, which is the upstream direction. **Figure 6** illustrates the trajectories of the actual and estimated angle of attack plotted versus time for a 75-second experiment under step inputs of the desired angle of attack. As the Bayesian filter estimation converges to the actual value, the servomotor steers the robotic fish to the desired orientation with a steady-state tracking error of less than 5 degrees.

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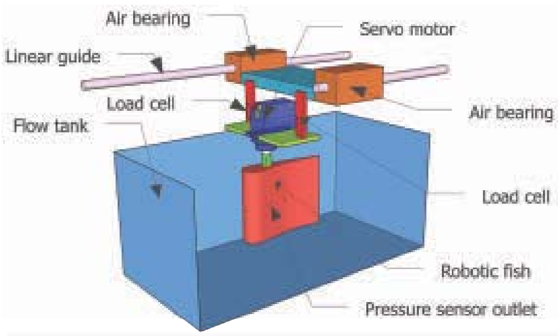


FIGURE 7 Schematic of the speed-control experimental testbed.

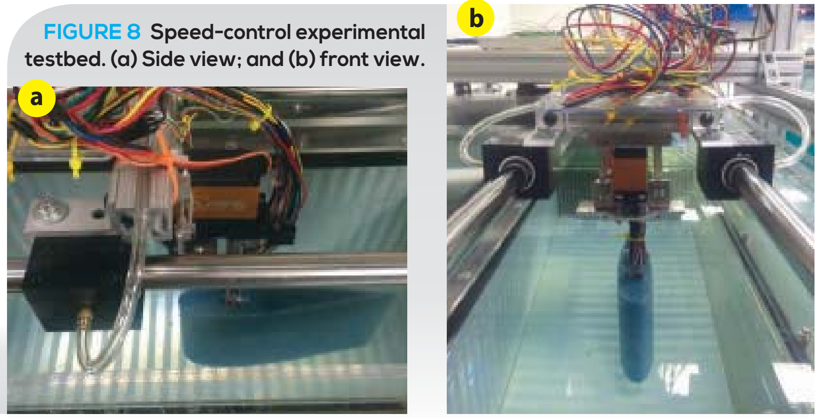


FIGURE 8 Speed-control experimental testbed. (a) Side view; and (b) front view.

SWIMMING-SPEED CONTROL

Closed-loop control of the flow-relative swimming speed plays an important role in fish predation and schooling behavior. We used the flexible, self-propelled robotic fish **(Figure 3)** to implement the speed-control behavior based on distributed flow estimation. A one-dimensional swimming testbed **(Figures 7** and **8)** includes air bearings to support the linear motion of the robotic fish in the along-stream direction. A servomotor driven in a periodic sinusoidal waveform controls the flapping motion, where the flapping amplitude and frequency are the control variables. The pressure measurement data is acquired using National Instruments DAQ 6225. The data is transmitted via USB to a laptop that runs the Bayesian filter for data assimilation and the closed-loop control, coded in Matlab 2013b. The control commands for the angle of attack are sent via serial communication to an Arduino UNO that drives the servo. The robotic fish demonstrated satisfactory control performance at a forward speed between 10 and 25 cm/s when actuated at a flapping frequency of 0.75 Hz. The steady-state speed tracking error was less than 5% and the convergence time less than two flapping periods **(Figure 9)**.

CONCLUSION AND ONGOING WORK

Bio-inspired flow sensing and flow-relative control using distributed sensor measurements were described and demonstrated with two underwater robots. Prototypes of the robotic fish were designed for experiments to include a rigid airfoil-shaped robot and a flexible, self-propelled robot. Flow past a Joukowski foil was modeled using quasi-steady potential flow theory and unsteady vortex-shedding techniques. The closed-loop control of the flexible robot comprised feedforward and feedback controls. Rheotaxis and speed-control experiments demonstrated the effectiveness of the flow sensing and control algorithms. In ongoing work, we are investigating a novel actuation approach using an internal reaction-wheel for flexible fish propulsion. ■

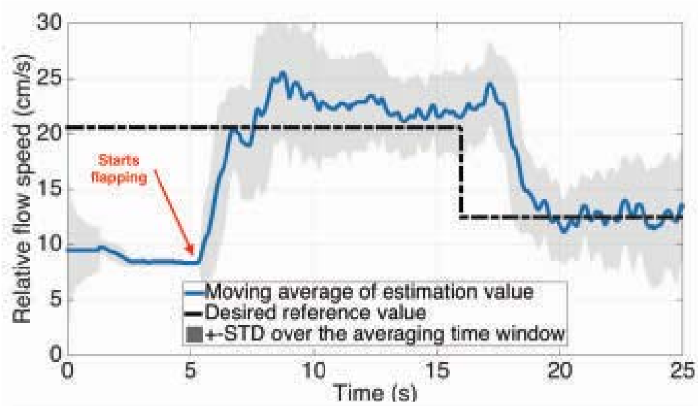
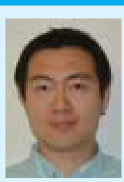


FIGURE 9 The moving average of flow-relative speed calculated using a time window equal to a single flapping period [8].

ABOUT THE AUTHORS



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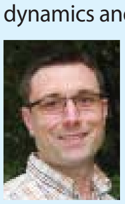
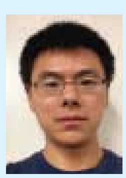


Francis D. Lagor is a Ph.D. student in the Department of Aerospace Engineering and Institute for Systems Research at the University of Maryland. Interests center around estimation, navigation and control of robotic systems in complex flow environments.



Hong Lei received the Ph.D. degree in electrical and computer engineering from Michigan State University in 2015, where he is currently a research associate. Research focuses on modeling of sensing properties and sensor application for IPMC materials.

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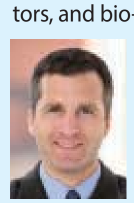

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