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Robotic Fish Localization and Tracking Using Simultaneous Perturbation-Neural Algorithm

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Abstract*— Fish and aquatic amphibians use the lateral line system, consisting of arrays of hair-like neuromasts, as an important sensory organ for prey/predator detection, communication, and navigation. In this paper a novel bio-inspired artificial lateral line system is proposed for underwater robots and vehicles by exploiting the inherent sensing capability of ionic polymer-metal composites (IPMCs). Analogous to its biological counterpart, the IPMC-based lateral line processes the sensor signals through a neural network. The effectiveness of the proposed lateral line was validated in localization of underwater motion source such as a flapping foil tail. In particular, as a proof of concept, a prototype with Body Length (BL) of 8 cm, comprising five millimeter-scale IPMC sensors, was constructed and tested. Experimental results showed that the IPMC-based lateral line could localize the sources from 4-5 BLs away, with a localization error comparable to source placement resolution at the source-sensor separation of 1 BL. In addition to the ease of fabrication, these results established the advantages of the proposed approach over other reported artificial lateral lines, in terms of both localization range and accuracy.

Index Terms—**Ionic polymer-metal composite (IPMC), lateral line system, robotic fish, source localization, neural networks.**

I. INTRODUCTION

Most fish and aquatic amphibians use the lateral line system as an important sensory organ to probe their environment [1], [2]. A lateral line consists of arrays of hair cell sensors, known as neuromasts. Each neuromast contains bundles of sensory hairs, encapsulated in a gelatinous structure called cupula, as illustrated in Fig. 1(a). An impinging flow deflects the cupula, and thus the hairs inside, eliciting firing of the hair cell neurons. Neuromasts can be divided into two types, superficial neuromasts, which are distributed on the skin surface, and canal neuromasts, which are recessed in the scales or in bony canals underneath the skin (Fig. 1(b)). With the same basic structure, the two types of neuromasts show distinct sensing characteristics [3]. The lateral line system allows an aquatic animal to identify near-field objects of interest and perform hydrodynamic imaging of the environment, typically within one to two Body Lengths (BLs) of the animal. Consequently, the lateral line is involved in various behaviors of aquatic animals, such as prey/predator detection [4], schooling [5], rheotaxis [6], courtship and communication [2]. In addition to the qualitative roles the lateral line plays in behaviors, there have been studies on how probed information is encoded and decoded in the nervous systems [7].

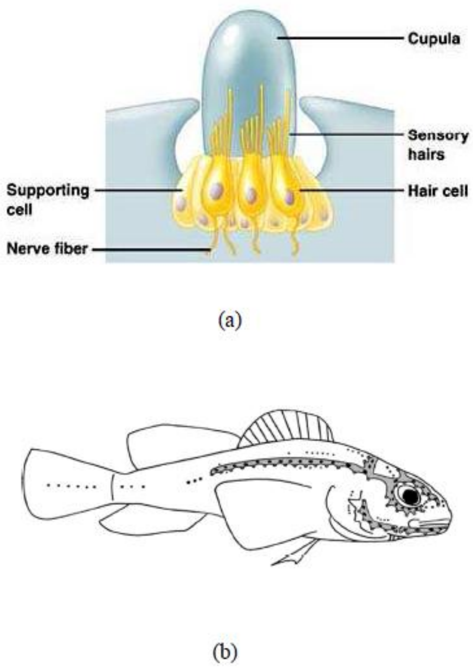

Fig.1. (a) Illustration of the structure of a neuromast (image credit: C.H. Mallery); (b) distribution superficial (small dots) and canal neuromasts (dots within shaded areas) on the Lake Michigan mottled sculpin [1].

The biological lateral line system has inspired the effort to engineer artificial lateral lines for applications in underwater vehicles and robots. Providing a stealthy complement to existing sensing modules, such as cameras and sonar's, artificial lateral lines can potentially provide information on flow conditions, obstacles, and moving objects for underwater robots and vehicles. This in turn can enable stabilization in response to turbulent currents or choppy waves, energy-saving in locomotion, navigation, and collaborative behaviors such as schooling. On the hardware side, arrays of flow sensors, explicitly motivated by the biological lateral line, have been fabricated based on various transduction principles, such as hot wire anemometry [8], piezoresistivity/strain gauge [9], [10], and capacitive sensing [11]. On the signal processing, side, researchers have mainly examined the problem of localizing a vibrating sphere, known as a dipole. Dagamseh *et al.* proposed the use of characteristic points (zero-crossings, maxima, etc.) in the measured velocity profile for dipole source localization [11], similar to what was proposed by Franosch *et al.* for modeling the localization by the clawed frog *Xenopus* [12]. However, this approach would require prohibitively many sensors to determine the characteristic points, and it is limited to a maximum detection distance of 1/p2 BL. Data-matching approaches were presented by Pandya *et al.*, where the measured signal pattern was compared with a large, pre-obtained set of templates or a model fitted with sufficient amount of data [13]. These approaches suffered from the need for excessive computing and storage resources, or the difficulty in system-level implementation [13]. Recently, a beam forming algorithm for array signal processing was used to localize a dipole source and a flicking fish tail [10]. With a sensor-source separation of 0.5 BL, the resulting mean estimation error is between 0.1 and 0.2 BL. The contribution of this paper is a novel approach to the development of artificial lateral lines based on a novel class of soft smart materials, called ionic polymer-metal composites (IPMCs). We report, to our best knowledge, *the first* IPMC-based artificial lateral line system, including prototype development, sensor signal processing, and demonstration in the application of robot like fish localization. As a proof of concept, a prototype with Body Length (BL) of 8 cm, comprising five millimeter-scale IPMC sensors, was constructed. In analogy to the neural system for biological fish, an artificial neural network was proposed for processing the signals from the IPMC sensor array because of its ability to model the highly nonlinear relationship between the stimulus and the resulting flow field/sensor output. The use of the proposed artificial lateral line was demonstrated in the localization of a fish tail source. One type of vibrating stimuli was considered, a flapping foil that emulates a fish tail. Experimental results showed that the IPMC-based lateral line could localize the sources from 4-5 BLs away, with a localization error comparable to source placement resolution at the source-sensor separation of 1 BL. In addition to the ease of fabrication, these results established the advantages of the proposed approach over other reported artificial lateral lines, in terms of both localization range and accuracy. The results also confirmed the ability of the simultaneous perturbation neural network-based processing in capturing the highly nonlinear and complex relationship between source location and the sensor responses, with relatively few parameters.

II. EXPERIMENTAL SETUP AND SENSOR CHARACTERIZATION

A. *Experimental Setup*

The proposed artificial lateral line uses ionic polymer-metal composite (IPMC) material as the sensing elements. As illustrated in Fig. 2, an IPMC consists of three layers, with an ion ion-exchange polymer membrane (e.g., Nafion) sandwiched by metal electrodes. Inside the polymer, (negatively charged) anions covalently fixed to polymer chains are balanced by mobile, (positively charged) cations. An applied mechanical stimulus redistributes the cations inside an IPMC, producing a detectable electrical signal (typically open-circuit voltage or short-circuit current) that is correlated with the mechanical stimulus (Fig. 2), which explains the sensing principle of IPMCs.

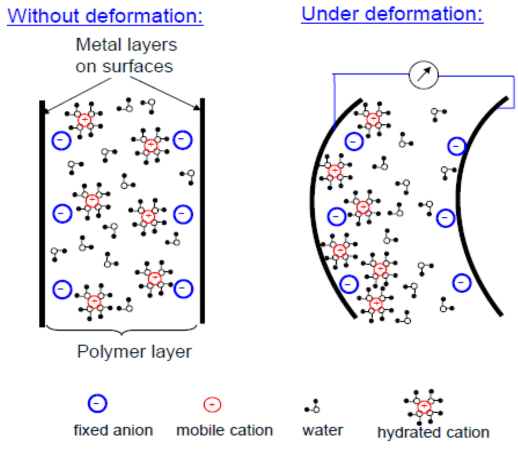

Fig.2. Illustration of IPMC sensing principle.

Fig. 3 shows the constructed lateral line prototype, consisting of five IPMC sensors. Each sensor, with dimensions 8 mm × 2.5 mm × 200 μm, was cut from an IPMC sheet fabricated by the Smart Microsystems Laboratory at Michigan State University, following a recipe similar to the one described in [14]. The sensor-to-sensor separation was 2 cm, resulting in a total span of 8 cm, which will be regarded as the Body Length (BL) in later analysis. Under a mechanical stimulus, an open-circuit voltage or a short-circuit current can be measured across the two electrodes of an IPMC. We have chosen to take the short-circuit current as the sensor output because current measurement is less susceptible to noises. Fig. 4 shows the schematic of the measurement circuit, which consists of two cascaded operational amplifiers (op-amps). Since the "−" terminal of Op-amp 1 is virtually the ground, the two electrodes of IPMC are short-circuited. The sensing current generated under this configuration, $i(t)$, is proportional to the voltage output $v_1(t) = R_1 i(t)$. The second op-amp is introduced for gain adjustment, where the resistor R_3 is tunable. The output $v_2(t)$ is related to the current signal $i(t)$ via $v_2(t) = R_3 R_1/R_2\, i(t)$. In the circuit we used, R_1 = 470 kΩ, R_2 = 10 kΩ, and R_3 was adjustable from 0 to 50 kΩ. Acquisition and processing of the IPMC sensor output were conducted through a dSPACE system (DS1104, dSPACE, Germany). In particular, a digital low-pass filter was further implemented to remove high-frequency noises.

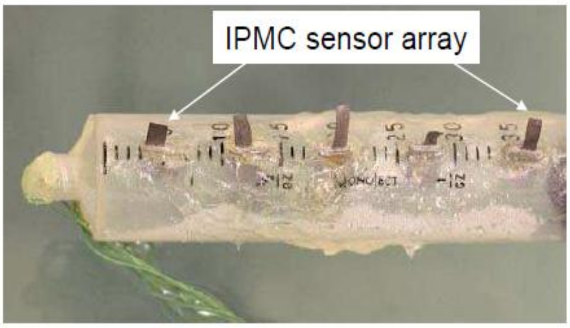

Fig.3. The IPMC-based lateral line prototype

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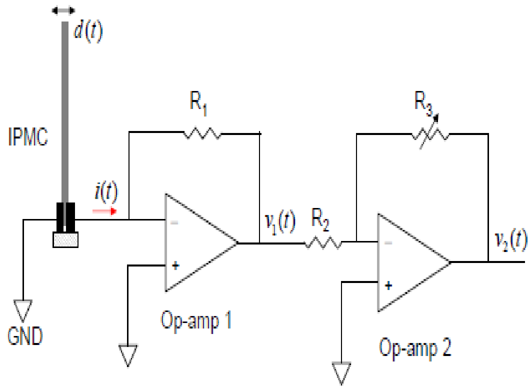

Fig.4. Circuit for measuring the short-circuit current generated by the IPMC sensor.

All experiments were conducted in a water tank measured 6×2×2 ft3. The source of stimulus used in the experiments was a flapping foil, driven with a servo motor and attached as the tail of a robotic fish, as shown in Fig. 5. The frequency and amplitude of the stimulating source can be controlled easily. The frequency range of the flapping tail spanned 0.5–5 Hz. The source location and vibration direction with respect to the IPMC lateral line could be adjusted by moving the stand holding the IPMC lateral line or by moving the source itself.

B. Sensor Characterization

Fig 6 shows a typical sensor response under the flapping tail stimulation (3 Hz), indicating that the current output from the IPMC sensor was at the order of nA, which could be captured very well by the sensing circuit. For a given IPMC sensor, we also placed the dipole and flapping tail at different locations in the tank and measured the corresponding amplitudes of sensor output. Fig 7 shows the amplitude of measured sensor output as a function of the stimulus location, for flapping tail stimuli. It can be seen that, while in general the signal gets stronger when the source gets closer, the overall amplitude landscapes have sophisticated profiles. The results in Fig. 7 clearly illustrate the challenge in underwater localization. In particular, it would be difficult to localize unambiguously a source with a single sensor; instead, a lateral line-like array structure will be needed.

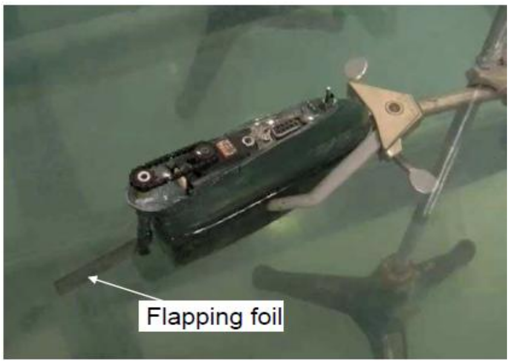

Fig.5 Stimuli sources used for the lateral line sensor: a flapping foil.

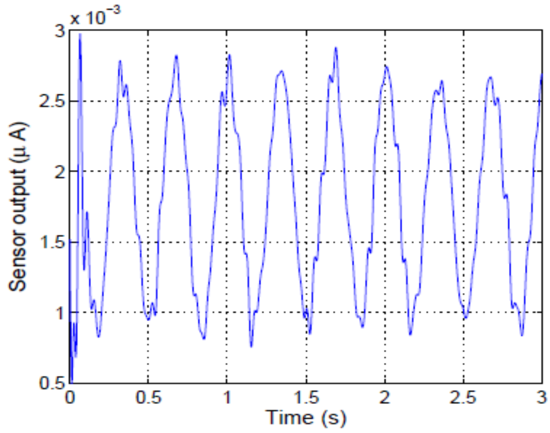

Fig.6. A typical IPMC sensor signal, showing clear periodicity of the source

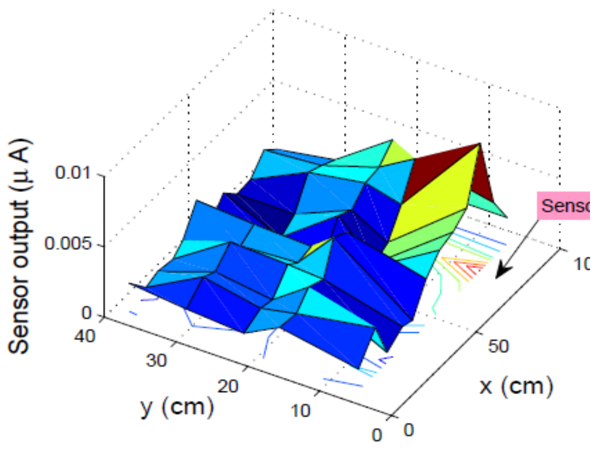

Fig.7. Measured sensor signal amplitude as a function of source location: flapping tail stimulation. The signal was from a single IPMC sensor, the location of which was marked in the figures

III. SOURCE LOCALIZATION USING SIMULTANEOUS PERTURBATION NEURAL NETWORK

The signals from IPMC sensors of the artificial lateral line are complex functions of the source location, because of nonideal fluid conditions and interactions of fluid with structures (e.g., the IPMC beams and the walls of the tank). In addition, the sensing characteristics of individual sensors could be different from each other in practice because of imperfect fabrication processes and variations in dimensions. The sensor outputs are further contaminated with noises due to ambient water movement and thermal fluctuations [15]. As a result, it is difficult to decode the sensor signals analytically. Biological fish are faced with similar challenges in extracting relevant sensing information from vast amount of data that are corrupted by noises. However, they manage to accomplish source localization and other missions robustly through neural network-based information processing. Taking this biological inspiration, we constructed an (artificial) neural

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network to process the signals acquired by the IPMC-based lateral line. As illustrated in Fig. 8, we adopted the multilayer perceptron (MLP) architecture for the neural network. An MLP network consists of an input layer, a hidden layer, and an output layer, and is the most widely used network structure for nonlinear classification and prediction applications [16]. One could use different features extracted from the sensor output data as the input to the neural network. In this work, we used the signal amplitude at the stimulus frequency because of its robustness to measurement noises. The amplitude was obtained through fast Fourier transform (FFT). The number of inputs was the same as the number of IPMC sensors considered. For comparison purposes, in this work we investigated the performance of the artificial lateral line when different numbers of sensors were adopted. The number of the hidden layer nodes was chosen through a simultaneous perturbation algorithm (SP)-based optimization process, which will be further described below.

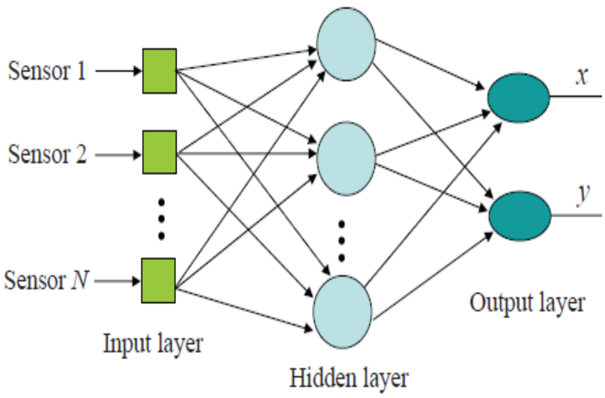

Fig.8. Schematic of the MLP neural network for signal processing of the IPMC lateral line

Each hidden layer node represents the operation of nonlinear activation, which takes the form of a sigmoid function. The output layer has two nodes, representing the x and y coordinates of the vibrating source. The number of hidden-layer nodes and the connective weights between the layers were determined through a two phase training procedure, [17]. The training data were obtained by placing the stimulus at known locations (x_i, y_i), $1 \le i \le M$, measuring the corresponding sensor outputs and computing the signal amplitudes. Here M is the number of training data. In the first training phase, a simultaneous perturbation was used to find an appropriate value for the number of hidden layer nodes and a reasonable set of values for the connective weights. In particular, each genome encoded both the number of hidden-layer nodes and the weights of all connecting edges. The maximum number of hidden-layer nodes was limited to 8 based on the numbers of network inputs and outputs. The values of the connective weights obtained in the first training phase then served as the initial condition for weights refinement in the second phase, where the network structure was fixed as determined in the first phase. Delta-bar-delta learning [16], with adaptive learning rate, was used for weights optimization. Let K be the total number of weights. For each weight w_k, $1 \le k \le K$, the update rule is

$$w_k^{new} = w_k^{old} - \eta_k^{new} \frac{\partial J}{\partial w_k^{old}}, \qquad (1)$$

where the adaptive learning rate η_k is updated as

$$\eta_k^{new} = \begin{cases} \eta_k^{old} + a, & if \ \dfrac{\partial J}{\partial w_k^{old}} > 0 \\ \eta_k^{old}, & if \ \dfrac{\partial J}{\partial w_k^{old}} < 0 \end{cases}, \qquad (2)$$

and $0 < a, b < 1$ are constants.

IV. EXPERIMENTAL RESULTS

We performed localization experiments for the flapping tail stimulus. As shown in Fig. 9, the working area was extended to about 40 × 100 cm^2 and a total of 60 training points was used. Validation was performed at 37 points along four tracks. The tail was flapping at 3 Hz. Fig. 10 shows more detailed validation results. The prediction error was roughly twice that of the dipole case [18], [19], which could be explained by the larger working area, fewer training points, and more sophisticated hydrodynamics created by the tail than that by the dipole.

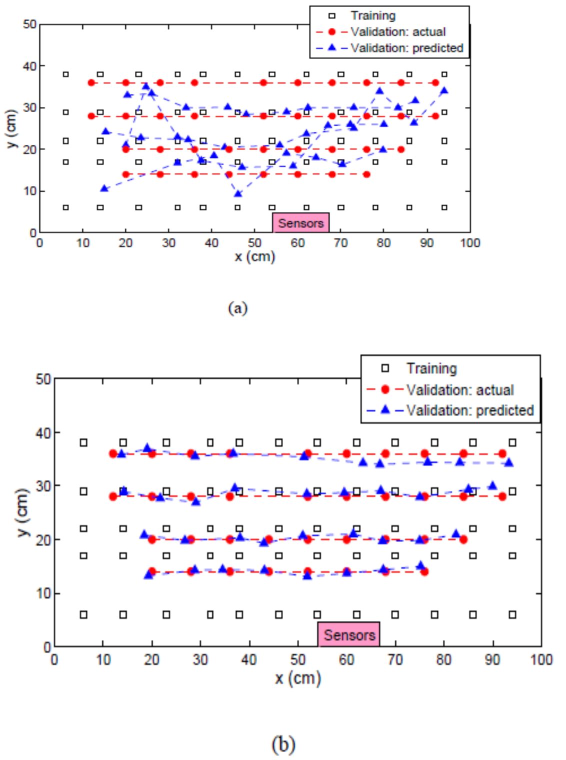

Fig.9. Localization of the flapping tail source using the lateral line: (a) One IPMC sensor as the input to the neural network; (b) three IPMC sensors as the input to the neural network

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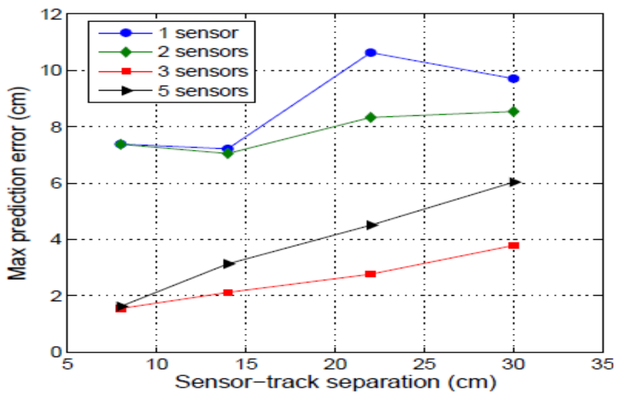
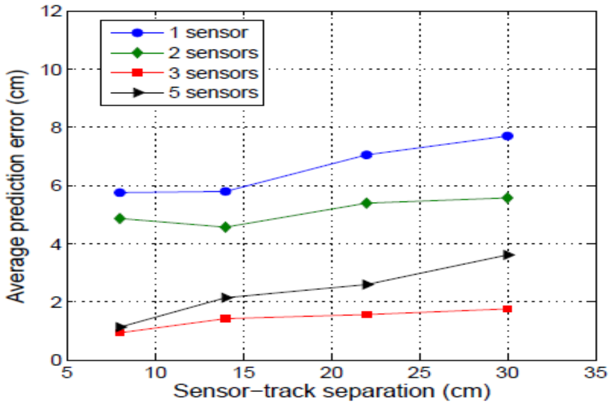
V. CONCLUSION

The contribution of this paper was a new approach to the realization of artificial lateral lines for underwater robots and vehicles, including both the proposal of using IPMC materials as sensing elements and the neural network-based signal processing algorithm. The effectiveness of the proposed approach was validated in experiments involving localization of a flapping tail. Experimental results showed that, with relatively few sensor elements, the IPMC-based lateral line was able to localize robot like fish at least 4-5 BLs away, and the localization accuracy at source-sensor separation of 1 BL was comparable to the resolution of placing the source. The approach thus demonstrated advantages in both the range and precision of localization over other reported methods for realizing artificial lateral lines.



(a)



(b)

Fig.10. Error in localization of the flapping tail source using the lateral line: (a) Maximum error along the track; (b) average error along the track

For future work, the proposed approach will be extended in several directions. First, we will explore the additional phase information in the sensor signals to further improve the localization performance. Extension will also be made to track moving robotic fish, where the received signals may not be at their steady state and insufficient data are available for FFT calculation. Finally, we will mount the IPMC-based lateral line on a swimming robotic fish, such as the one reported in [20], and investigate the processing schemes for the lateral line to decouple external signals from self-motion-induced flow signals.

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