Fish lateral line inspired perception and flow-aided control: 
A review

Yufan Zhai1, Xingwen Zheng1, Guangming Xie1,2,3

1 State Key Laboratory for Turbulence and Complex Systems, Intelligent Biomimetic Design Lab, College of Engineering, Peking University, Beijing, 100871, China
2 Institute of Ocean Research, Peking University, Beijing, 100871, China.
3 Peng Cheng Laboratory, 518055 Shenzhen, China.

E-mail: zhengxingwen@pku.edu.cn; xiegming@pku.edu.cn

June 2020

Abstract. Any phenomenon in nature is potential to be an inspiration for us to propose new ideas. Lateral line is a typical example which has attracted more interest in recent years. With the aid of lateral line, fish is capable of acquiring fluid information around, which is of great significance for them to survive, communicate and hunt underwater. In this paper, we briefly introduce the morphology and mechanism of the lateral line first. Then we focus on the development of artificial lateral line which typically consists of an array of sensors and can be installed on underwater robots. A series of sensors inspired by the lateral line with different sensing principles have been summarized. And then the applications of artificial lateral line system in hydrodynamic environment sensing and vortices detection, dipole oscillation source detection, and autonomous control of underwater robots have been surveyed. In addition, the existing problems and future foci in the field have been further discussed in detail. The current works and future foci have demonstrated that artificial lateral line has great potentials of research and contributes to the applications of underwater robots.

Keywords: lateral line; artificial lateral line; flow sensor; flow-aided control; underwater robot

1. Introduction

Comparing with extracting land resources, it’s more difficult to exploit marine resources. Due to the complexity of underwater environment, the causticity of the seawater, the high pressure of the deep seafloor, the poor visibility in the sea, and the strong interference to the sensors, people are facing extremely harsh conditions when exploiting marine resources. With the rapid development of machine manufacturing and artificial intelligence, robots serve significant functions in resource exploitation.

However, the development of underwater robots is more difficult than that of land robots because of the above-mentioned reasons. With the further development of marine resources, the disadvantages of traditional underwater robots are gradually highlighted: large size,
Figure 1: The graphical abstract of this article.
complex system, low control flexibility, high energy consumption, low efficiency, and lack of autonomy.

Biomimetics which acts as a new comprehensive subject provides another way for underwater robot manufacturing. Many researchers have taken inspiration from aquatic organisms and developed new underwater robots from the bionic perspective, commonly known as biomimetic underwater robots. For aquatic organisms, they have lived in marine environment for billions of years and adapted to the environment through evolution. They have the advantages of high maneuverability, high sensitivity to changes in surrounding environment and high energy efficiency, etc. Inspired by the excellent performance mentioned above, various kinds of biomimetic underwater robots have been developed successfully: robotic fish [1] [2] [3] [4], robotic dolphin [5], robotic snake [6], robotic turtles [7], robotic salamanders [8], etc.

Owing to the complexity of underwater environment, robots must be equipped with well-developed underwater sensing system, which can help them to adapt to the environment and perform underwater tasks. Due to the particularity of water environment, land sensors cannot be directly used under the water, which restricts the development of sensing technology for underwater robots to some extent. To solve this problem, scientists have taken inspiration from marine life once again. Over billions of years of evolution in the ocean, fish have developed advanced systems for sensing the water environment. Lateral line is such a unique sensing system of fish and plays a key role for fish behaviours in complex water environment. The research and development of artificial lateral line (ALL) system referring to an array of sensors installed on the underwater vehicle will greatly improve the perception ability of the robots, which is advantageous for underwater missions.

In this paper, we firstly describe the biology of lateral line and the models which have been established to illustrate the mechanisms in section 2. In section 3, we review the sensors that are inspired by the lateral line and based on different sensing principles according to the categories. In section 4, we present applications of ALL in hydrodynamic environment sensing and vortices detection. In section 5, we introduce results in dipole oscillation source detection with the help of ALL using different methods. Finally, we discuss the flow-aided control of underwater robots using ALL system for different purposes. At the end of the article, we discuss the problems of current studies and try to put forward possible improvement strategies for further studies. The structure of the article is shown in Figure 1. The abbreviations used in this article and corresponding full names are listed in Table 1.

Table 1: The abbreviations used in this article and corresponding full names

| Abbreviation | Full name                       |
|--------------|---------------------------------|
| AlN          | Aluminium Nitride               |
| AHC          | Artificial hair cell            |
| ALL          | Artificial lateral line         |
| CN           | Canal neuromast                 |
| CRB          | Cramer-Rao bound                |
2. Mechanisms and models of the fish lateral line

Lateral line is the most highly differentiated structure in the sensory organs of the skin, which is typically sulcus or tubular. It is a sensory organ peculiar to fish and aquatic amphibians and important for them to maneuver in the darkness [9]. The sensory unit of the lateral line is the neuromast, a receptor that consists of sensory hair cells and support cells [10]. There are two types of lateral line neuromasts: superficial neuromast (SN) and canal neuromast (CN), as shown in Figure 2. Both of these two kinds of neuromasts sense the stimulation generated by water flow through sensory cells. Due to the difference in distribution, number and morphology of sensory cells, the two kinds of neuromasts have different functions [11].

The SNs which act as displacement sensors are free-standing on the skin or on pedestals grown above the skin. They are usually located in lines on the fish body [13]. The ability of sensing the flow direction and velocity is mainly realized by the SNs which are sensitive to the displacement and respond to the low-frequency direct current component. When the water flow and the fish surface move relatively to each other, the SNs bend, causing the neuromasts below to produce nerve impulses which will be transmitted from nerve endings to the nerve centers of the brain. Under such a mechanism, fish can sense the flow information with the help of SNs. On the other hand, the CNs are equivalent to pressure gradient sensors which can sense pressure gradient and are sensitive to acceleration and respond to high-frequency components. The CNs are located in the lateral line canals that are full of mucus under the epidermis of fish and communicate with the external water environment through some small holes [14]. When there is a velocity gradient between adjacent holes, the pressure difference will be generated, leading to the fluid movement in the lateral line canals, which triggers
The first term of the left side in the Eq. (3) can be defined as:

\[ Y(t) = \frac{1}{2} \pi \rho a^3 f t \]

The first term of right side in the Eq. (3) is the stimulus frequency.

For the forces on the CNs, the governing equation can be described as:

\[ F_m + F_k = F_u + F_b \]

where \( F_m \) and \( F_k \) are the material and stiffness force, \( F_u \) is the drag force, and \( F_b \) is the buoyant force.

**Figure 2:** Lateral line and neuromasts of a fish. Black dots represent locations of SNs, and white dots show the approximate locations of canal pores. [12]

The lateral line system composed of CNs and SNs can sense various stimuli from different directions, so that fish can acquire enough information for a full sense of surrounding water environment.

**Figure 3:** Biomechanical model and force analysis for a CN. [15]

Scientists have established theoretical models to describe the sensing mechanisms of these neuromasts and to study the interactions between flow and fish, which is instructive to the development of ALL system. As shown in Figure 3, the CN can be regarded as a rigid hemisphere sliding over a frictionless plate in biomechanics which is coupled with a linear spring [15] [16]. For the forces on the CNs, the governing equation can be described as:

\[ F_m + F_k = F_u + F_b \]
The terms on the left are the inertial force and the structural stiffness resistance which can be written as the following forms respectively:

\[ F_m = M \frac{d^2 Y(t)}{dt^2} \]
\[ F_k = K Y(t) \]

where \( M \) represents the cupula mass, \( Y(t) \) represents the displacement induced by the passing flow, \( K \) is the sliding stiffness. The terms on the right are the hydrodynamic drag force and buoyant force due to the pressure difference which can be defined as the following forms:

\[ F_u = D [ \frac{dY(t)}{dt} - \frac{dW(t)}{dt} ] \]
\[ F_b = M \frac{d^2 W(t)}{dt^2} \]

where \( D \) is the drag coefficient, \( W(t) \) is the displacement of external flow. Thus \( \frac{dY(t)}{dt} - \frac{dW(t)}{dt} \) represents the relative velocity of the cupula and external flow. According to the above results, the governing equation can be written as

\[ M \frac{d^2 Y(t)}{dt^2} + K Y(t) = D [ \frac{dY(t)}{dt} - \frac{dW(t)}{dt} ] + M \frac{d^2 W(t)}{dt^2} \]

In order to describe the sensitivity of CNs, considering that the equation is linear, the displacement can be decomposed into different frequencies. At a certain frequency, \( Y(t) \) and \( W(t) \) are the steady-state oscillatory displacement and the oscillating flow displacement with a form of \( Y(t) = Y_0(f) e^{i2\pi f t} \) and \( W(t) = W_0(f) e^{i2\pi f t} \). So the velocity of the flow is expressed as

\[ V(t) = \frac{dW(t)}{dt} = i2\pi f W_0(f) e^{i2\pi f t} = V_0(f) e^{i2\pi f t} \]

The frequency-dependent sensitivity of the CNs is defined as the ratio of displace amplitude of cupula and the velocity amplitude of flow, which is shown in the following formula:

\[ S_{CN}(f) = \frac{Y_0(f)}{V_0(f)} = \frac{1 + \frac{\mu^2}{2} (1 + i) \sqrt{\frac{f}{f_t}} + \frac{1}{2} i \frac{f}{f_t}}{-2\pi f_t N_f + i \frac{f}{f_t} - \frac{\mu^2}{2} (1 - i) (\frac{f}{f_t})^2 - \frac{1}{2} (\frac{f}{f_t})^2} \]

where \( f_t \) is the transition frequency expressed as \( f_t = \frac{\mu}{2\pi \rho_a a^2} \) which determine viscous \((f < f_t)\) or inertial \((f > f_t)\) forces dominate the fluid forces applied on the cupula. \( \mu \) is the dynamic viscosity of fluid. \( N_f = \frac{K a \rho_\alpha}{6\pi \mu a^2} \) which represents the resonance properties is the resonance factor.

Different from the CN, the SN is modeled as two connecting beams with different bending rigidity, as shown in Figure 4. The distal beam is more flexible than the proximal beam because of the difference in material properties of the proximal and distal parts of cupula. A spring is used to simulate the torsional stiffness generated by the hair beam. The governing equation is different from that of CNs, forces applied on the beams are also functions of elevation \( z \) due to the uneven distribution of forces when a beam bends. The equation is expressed as

\[ F_m(z) + F_e(z) = F_u(z) + F_a(z) + F_b(z) \]
The terms from left to right represent the inertial force, elastic stiffness term, hydrodynamic drag force, acceleration reaction force and buoyant force respectively. Similar to CNs, the sensitivity of SNs is defined as the ratio of cupula deflection $v(H)$ at the height of the beam and free-stream velocity $U_\infty$, which is written as

$$S_{SN}(f) = \frac{v(H)}{U_\infty} = -\frac{ib_w}{2\pi fb_m}\left[1 - \frac{i\pi fb_m\delta^4}{2EI + i\pi fb_m\delta^4}\right]e^{-\frac{H(1+i)}{\delta}} + \sum_{j=0}^{3} C_j e^{iH^4\sqrt{\frac{2\pi fb_m}{EI}}}$$

where $C_j$ represents a sequence of four integration constants. $H$ is the height of the top of the beam. $EI$ is the bending modulus of the beam. $\delta$ is the thickness of boundary layer expressed as $\delta = \sqrt{\frac{2\mu}{\rho_o \omega}}$, where $\omega$ is the angular speed of the stimulus. More details on the parameters $b_m$ and $b_w$ can be referred to the paper [17].

Figure 5 shows the propagation path of lateral line neuromasts. On one hand, for CNs, the propagation path is divided into two steps. At the first step, the velocity or acceleration of the external free flow is converted into the velocity of the local flow with the help of the boundary layer and canals. Flow outside induces the pressure difference between the canals, which triggers flow velocity inside the canal. At the second step, canal flow applies fluid forces on the cupula and results in the CN deflection. On the other hand, for SNs, at the first step, the velocity or acceleration of the external free flow is converted into the velocity of the local flow similarly without the reflection of canal flow. At the second step, SNs deflects under the forces induced by local flow [15].

With the assistance of SNs and CNs, fish can detect the flow direction and speed and pressure gradients respectively. Moreover, SNs can distinguish fields in a spatial uniform flow and in a turbulent flow, while CNs only respond to a non-uniform flow field, such as the fluctuation of water produced by a vibrating sphere or a swimming fish.
Figure 5: Propagation path of lateral line neuromasts. (a) Propagation path of CNs. (b) Propagation path of SNs. [15]

3. The existing ALL sensors and systems

3.1. ALL sensor unit

As mentioned above, scientists have established mathematical models to interpret the mechanisms that how fish acquire fluid information assisted by lateral line. The results can be an inspiration of ALL. Owing to the limitations of existing technologies for underwater detection such as scattering and multipath propagation issues for acoustic sensors and turbidity of the sea for optical sensors [15], varieties of fish sensing organs inspired sensors were developed using different principles. Considering that commercial pressure sensors are not as sensitive as the lateral line receptors and the functions are limited, various kinds of self-developed ALL sensors have been explored. The existing ALL sensors are based on different sensing mechanisms, including piezoresistive, piezoelectric, capacitive, optical, thermal and magnetic effect. The research status of ALL sensors with different sensing mechanisms will be discussed below.

3.1.1. Piezoresistive ALL Sensors Piezoresistive sensor is a device based on the piezoresistive effect of the semiconductor material on the substrate. Piezoresistive effect refers to a phenomenon that the electrical resistance of the material changes while it is subjected to force. As a result, the bridge on the substrate produces corresponding unbalanced output. In this way, the substrate can be directly used as an element to measure pressure, tension and etc. And then based on the quantity measured directly, the information about the environment is available. Figure 6 shows various piezoresistive ALL sensors mentioned below.

In 2002, Fan et al. firstly made a major breakthrough in piezoresistive ALL sensors fabrication using combined bulk micromachining methods and an efficient three-dimensional
Figure 6: Various piezoresistive ALL sensors. (a) Scanning electron micrograph of a single artificial hair cell sensor [18]. (b) Scanning electron micrograph of an AHC sensor [19]. (c) The front-view of a hair sensor after being coated with the hydrogel material [20]. (d) Scanning electron micrograph on a bent cantilever [21]. (e) Scanning electron micrograph on a fabricated cantilever [22]. (f) An angle view of the complete sensor with hair cell [23]. (g) Photographic image of the final ALL canal system prototype [24]. (h) Cupula formed using nanofibrils scaffold has a prolate spheroid shape [25]. (i) Diagram of the pressure sensor array with basic structure depicted [26]. (j) Photograph of the pressure sensor array [27]. (k) Optical microscopic image of a fabricated full-bridge LCP sensor with two radial and two spiral gold piezoresistors [28].
assembly method named plastic deformation magnetic assembly (PDMA) process. They leveraged PDMA to realize the vertical cilium, which was important in the hair cell. A single sensor was composed of an in-plane fixed-free cantilever mainly made of Boron ion diffused Si using etching technology, a vertical artificial cilium attached at the free end and a strain gauge located at the base of the horizontal cantilever which was used to sense the bending of the vertical cilium. Subjected to the impact of local flow, the vertical cilium bent and transferred the influence to the cantilever beam. The corresponding results were measured by the strain gauge. The sensors were used to detect laminar flows ranging from 0.1 to 1 m/s [18].

In 2003, Chen et al. compared the above sensor with the hot-wire anemometer and improved the design by rigidly connecting the vertical hair to the substrate and placing the strain gauge at the root of the hair directly, which made an advance in the spatial resolution of the sensor [29]. In order to further improve the sensitivity and resolution, in 2007, Yang et al. proposed another highly sensitive piezoresistive flow sensor fabricated on a Silicon-on-insulator (SOI) wafer, the cilium of which was made of photodefimable SU-8 epoxy and adopted a symmetric cylindrical shape. The sensor was used to detect the steady-state laminar flow and oscillatory flow with a threshold down to 0.7 mm/s [19] [30] [31]. In 2010, they assembled piezoresistive sensors on the surface of a cylindrical polyvinyl chloride (PVC) model and put forward an adaptive beamforming algorithm in order to locate the dipole source [32].

To match the threshold sensitivity of the integrated fish flow sensory system, McConney et al. created a bio-inspired hydrogel-capped hair sensory system in 2008 using a precision drop-casting method. They added extremely compliant and high-aspect-ratio hydrogel cupula (polyethylene glycol) to the SU-8 hair sensors, as a result of which, the sensitivity of the sensors was enhanced by about two orders of magnitude (2.5 µm/s) [20].

Unlike the sensors mentioned above whose material was mainly silicon, Qualtieri et al. reported on a kind of ALL sensor in 2011, the key component of which was the stress-driven Aluminium Nitride (AlN) cantilevers. The structures utilizing a multilayered cantilever AlN/Molybdenum (Mo) and a Nichrome 80/20 alloy as piezoresistor were realized by means of micromachining techniques combining optical lithography and etching process. The piezoresistor showed a sensitivity to directionality and low value pressure with a detection threshold of 0.025 bar [21]. Besides, in 2012, they deposited a water resistant parylene conformal coating on the hair cell and developed a biomimetic waterproof Si/SiN multilayered cantilever using surface micromachining techniques. The sensor showed mechanical robustness in high-speed flow and had the capability of discriminating the flow direction at low frequencies [22].

In 2014, Kottapalli et al. developed an artificial SN sensor array composed of a liquid crystal polymer (LCP) membrane, a gold strain gauge and a Si-60 cilium fabricated by stereolithography with a high-aspect ratio of 6.5. The sensors demonstrated a high sensitivity of 0.9 mV/(m/s) and 0.022 V/(m/s) while detecting air and water flows. And the threshold velocity limits were 0.1 m/s and 15 mm/s, respectively [23]. In 2016, they created a canopy-like nanofiber pyramid around the Si-60 polymer cilium and then dropped the casting hydrogel cupula onto the nanofiber scaffold to enhance the sensors. The velocity detection threshold of
the sensor was 18 mm/s while it is used in water flow sensing [25].

All sensors mentioned above feature a cilium and a cantilever beam, which bends under the impact of water flow and is sensitive to flow velocity. Except for this, other piezoresistive sensors are mostly planar and the piezoresistors are directly installed on the substrate to detect underwater pressure distribution and variations.

In 2017, Jiang et al. integrated cantilevered flow-sensing elements mainly made of polypropylene and polyvinylidene fluoride (PVDF) layers in a polydimethylsiloxane (PDMS) canal and used it to detect a dipole vibration source. The sensors showed high-pass filtering capability and a pressure gradient detection limit of 11 Pa/m at the frequency of 115 Hz [24]. Additionally, Vicente et al. used an array of off-the-shelf pressure sensors to detect cylindrical obstacles of round and square in 2007. The array consisted of hundreds of micro-electromechanical systems (MEMS) pressure sensors which were fabricated on etched Silicon and Pyrex wafers. A strain gauge was mounted on a flexible diaphragm which was a thin (20 µm) layer of Silicon attached at the edges of a square Silicon cavity with a width of 2000 µm and served as the sensing element with a pressure detection threshold of 1 Pa [26]. In 2012, they presented a 1-D array of four sensors with a 15-mm center-to-center spacing. Each sensor had two key components: a strain-concentrating PDMS diaphragm and a resistive strain gauge made of a conductive carbon-black PDMS composite. And the resolution of it was 1.5 Pa [27].

To perform underwater surveillance, Kottapalli et al. developed an array of polymer MEMS pressure sensors fabricated with a Cr (20 nm)/Au (700 nm) thick gold layer sputtered on a flexible substrate and LCP serving as the sensing membrane material. Installed on curved surfaces of the underwater vehicle bodies, the sensor detected underwater objects by sensing the pressure variations. Compared with Silicon-based hair vertical structures or thin metal cantilever beams, it showed a better sensitivity of 14.3 µV/Pa and a better resolution of 25 mm/s in water flow sensing [28].

3.1.2. Piezoelectric ALL Sensors  Piezoelectricity refers to the electric charge generated on the surface of some certain materials while subjected to external forces. This effect inspires another kind of ALL sensors which is able to sense environment by collecting the electric information. Figure 7 shows various piezoelectric ALL sensors mentioned below.

For the performance of situational awareness and obstacle avoidance, Asadnia et al. used floating bottom electrode to design an array of Pb(Zr0.52Ti0.48)O3 thin-film piezoelectric pressure sensors in 2013 [33]. Packaged into an array of 25 sensors on a flexible liquid crystal polymer substrate patterned with gold interconnects, the array was used to locate a vibrating sphere dipole in water and showed a resolution of 3 mm/s in detecting oscillatory flow velocity. Besides, the sensors had many advantages such as self-powered, miniaturized, light-weight, low-cost and robust. In 2015, they optimized the sensor by mounting a stereolithographically fabricated polymer hair cell on microdiaphragm with floating bottom electrode. The sensors demonstrated a high-pass filtering nature with a cut-off frequency of 10 Hz, a high sensitivity of 22 mV/(mm/s) and a resolution of 8.2 mm/s in water flow detection [36]. In 2016, they reported the development of a new class of miniature all-
polymer flow sensors with an artificial ciliary bundle fabricated by combining bundled PDMS micro-pillars with graded heights and electrospinning PVDF piezoelectric nanofiber tip links. By means of precision drop-casting and swelling processes, a dome-shaped hyaluronic acid hydrogel cupula encapsulating the artificial hair cell bundle was formed. The sensors achieved a sensitivity of 300 mV/(m/s) and a threshold detection limit of 8 µm/s respectively [34].

In 2011, Abdulsadda et al. proposed a novel ALL sensors utilizing the inherent sensing capability of ionic polymer-metal composites (IPMCs). An IPMC consisted of three layers, with an ion-exchange polymer membrane sandwiched by metal electrodes. Detectable electrical signals were produced under the impact of external forces. The IPMC flow sensor were used to localize dipole sources 4-5 body away and demonstrated a threshold detection limit of less than 1 mm/s [35].

3.1.3. Capacitive ALL Sensors Owing to the high sensitivity and low power consumption, capacitance principle has been widely used in many different types of sensors. The key component is the capacitive readout which has the capability of converting external stimulus into capacitance changes, which provides an effective way to detect underwater pressure and flow velocity. Like the piezoresistive sensors, the hair attached to the membrane will respond to the impact from the local flow. And then the membrane reflects and changes the distance or gap between the electrodes. As a result, the change in capacitance is quantitatively related to the external impact. Figure 8 shows various capacitive ALL sensors mentioned below.

In 2007, Krijnen et al. reported developments in hair sensors based on mechanoreceptive sensory hairs of crickets using artificial polysilicon technique to form Silicon Nitride-suspended membranes and SU-8 polymer processing for hairs with diameters of about 50 µm and up to 1 mm in length. The membranes havd thin chromium electrodes on top which formed variable capacitors and the sensitivity of the sensor is 1.39 pF/rad [37] [39]. In 2010, they realized the dense arrays of fully supported flexible SU-8 membranes with integrated electrodes underneath that supported cylindrical hair-like structures on the top. While used in air flow detection, the mechanical sensitivity at the frequency of 115 Hz was
Figure 8: Various capacitive ALL sensors. (a) Scanning Electron Microscope image of actual sensors [37]. (b) Top views of the ALL sensor [38].

0.004 rad/(m·s) [40].

Another capacitive whisker sensor inspired by seal vibrissae was developed by Stocking et al. to measure the flow velocity and detect the direction in 2010. They mounted a rigid artificial whisker on a novel cone-in-cone parallel-plate capacitor base which was covered by a PDMS membrane. Numerical simulation predicted the change of capacitor output signal in a range of 1 pF when the flow velocity varied from 0 to 1.0 m/s [38].

3.1.4. Optical ALL Sensors  Optical principles have also been used to develop ALL sensors. Figure 9 shows various optical ALL sensors mentioned below. Klein et al. made a great breakthrough in this area in 2011. The artificial canal neuromasts segment they developed consisted of a transparent silicone bar which had the same density of water and an infrared light emitting diode at one end of the silicone bar. To detect the fluid motion, light, leaving the opposite end of the silicone bar, illuminated an optical fiber that was connected to a surface mounted devices (SMD) phototransistor and the output was amplified and converted to be stored on a computer. The sensors are used to detect water movements caused by a stationary vibrating sphere or a passing object and vortices caused by an upstream cylinder. According to the acquired information, they calculated the bulk flow velocity and the size of the cylinder producing the vortices. The detection limit in water flow was 100 µm/s [41].

Figure 9: Various optical ALL sensors. (a) Scheme of an artificial CN [41]. (b) Scanning-Electron Microscope image of a pillar array [42]. (c) The photograph of the all-optical sensor [43].
Another method was put forward by Wolfgang et al. in 2009. The key component of the sensor was flexible micro-pillars which protruded into local flows and bent subjected to exerted drag forces. The pillar was fabricated from the elastomer PDMS and the deflection was measured by means of optical methods [42].

In 2018, Wolf et al. presented an all-optical 2D flow velocity sensor consisting of optical fibres inscribed with Bragg gratings supporting a fluid force recipient sphere. The artificial neuromast demonstrated a threshold of 5 mm/s at a low frequency and 5 µm/s at resonance with a typical linear dynamic range of 38 dB at 100 Hz sampling. Additionally, the artificial neuromast is capable of detecting flow direction within a few degrees [43].

3.1.5. Hot-Wire ALL Sensors Hot-wire anemometer (HWA) uses a heated wire placed in the air. While air or water flows through it, heat loss leads to changes in temperature and resistance. Therefore, we can measure the velocity by detecting electrical signals. Figure 10 shows various hot-wire ALL sensors mentioned below.

![Figure 10: Various hot-wire ALL sensors. (a) An optical micrograph of an ALL [44]. (b) A sensor unit [45].](image)

In 2006, Yang et al. developed a surface-micromachined, out-of-plane ALL sensor array using the principle of thermal HWA. Inspired by the SNs of fish, the hot wire was lifted from the substrate by two pointed heads. They utilized photolithography technique to fabricate the sensor in plane and assembled it outside by three-dimensional magnetic assembly. The sensor afterwards was used to track the position of a vibrating dipole source and exhibited a threshold of 0.2 mm/s with a bandwidth of 1 kHz [46] [44] [47].

Liu et al. proposed a novel micromachined hot-film flow sensor system realized by using a film depositing process and a standard printed circuit in 2009. They preprinted the sensor electrodes and electronic circuits on a flexible substrate of polyimide and utilized Cr/Ni/Pt as the sensing element with a resistance temperature coefficient around 2000 ppm/K. The resolution of this sensor was 0.1 m/s [45].

3.2. ALL sensors placement optimization

With the development of ALL sensors unit, more efforts have been devoted to the sensors placement optimization in order to simulate the fish lateral line to a greater extent. Verma et al. used a larva-shaped swimmer exposed in disturbances induced by oscillating, rotating
and cylinders to conduct experiments in 2020. Combining Navier-Stokes equations with Bayesian experimental design and with a purpose of detecting the location of the source, they presented that shear sensors should be installed on the head and the tail while pressure sensors should be distributed uniformly along the body and intensively on the head, which is similar to real fish lateral line [48]. In 2019, Xu et al. put forward an optimal weight analysis algorithm combined with feature distance and variance evaluation and 3 indexes to evaluate the performance of the sensor array. They also briefly discussed the optimal number of sensors [49]. This work has provided new ideas for studies in ALL sensors distribution optimization in the future.

In this section, we have presented ALL sensors based on different sensing mechanisms and briefly introduced works in sensors placement optimization. Table 2 summarizes the parameters of the ALL sensors, including transduction mechanism, processing technique, material and sensitivity. Though great progress has been made in the design and fabrication of ALL sensors, the sensors mentioned above are mostly simple imitations of the real fish lateral line and have a long way to go in sensitivity. Firstly, the sensitivity of a single sensory unit can be further improved. Additionally, the neuromasts distribution of fish is continuously optimized in evolution. Thus, it is necessary for us to find out the optimal distribution of ALL sensors according to different shapes of robotic fish in order to simulate the lateral line to the maximum extent possible and develop a complete ALL system based on existing local sensor arrays. Last but not least, we need more efficient signal processing methods to take full advantage of the information acquired by the ALL system and make decisions like a living body. ALL system like this has great potential for future oceanographic research.

**Table 2: Summary of ALL sensors**

| Transduction mechanism | Author | Processing technique | Material | Sensitivity |
|------------------------|--------|----------------------|----------|-------------|
|                        | Fan et al. 2002 [18] Chen et al 2003 [29] | PDMA for vertical cilium, micromachining | Boron ion diffused Si for piezoresistor, Metal-permalloy for hair | 100 mm/s |
|                        | Chen et al. 2007 [19] Yang et al. 2007 [30] Chen et al. 2006 [31] Yang et al. 2010 [32] | Ion implantation, deep reactive ion etching | Boron ion diffused Si for piezoresistor, SU-8 epoxy for hair | 0.1 mm/s |
| McConney et al. 2008 [20] | Photo polymerization | Boron ion diffused Si for piezoresistor, SU-8-hydrogel for hair | 2.5 μm/s |
|--------------------------|----------------------|---------------------------------------------------------------|----------|
| Qualtieri et al. 2011 [21] | Micromachining | Aluminum Ni for piezoresistor, Nichrome alloy for hair | 0.025 bar |
| Qualtieri et al. 2012 [22] | Micromachining | Si/SiN for piezoresistor, Parylene for hair | 50 mm/s |
| Kottapalli et al. 2014 [23] | Deep reactive ion etching, electrostatic spinning | LCP for membrane, gold for strain gauge, Si-60 for hair, HA-MA hydrogel for cupula | 100 mm/s (air), 18 mm/s (water flows) |
| Jiang et al. 2017 [24] | Micromachining | PDMS for canal, Polypropylene and PVDF for piezoresistor | 11 Pa/m |
| Vicente et al. 2007 [26] | Micromachining | Si | 1 Pa/m |
| Vicente et al. 2012 [27] | Micromachining | PDMS for diaphragm, a conductive carbon-black PDMS composite for strain gauge | 1.5 Pa |
| Kottapalli et al. 2012 [28] | Micromachining | LCP for membrane, gold for piezoresistors | 25 mm/s |

**Piezoelectric**

| Asadnia et al. 2013 [33] | Micromachining and the sol-gel method | Pb(Zr0.52Ti0.48)O3 for membrane, Si-60 for hair | 3 mm/s |
| Asadnia et al. 2015 [36] | Precision drop-casting and swelling processes | PDMS for micro-pillars, PVDF for tip links, HA-MA hydrogel for cupula | 8 μm/s |
| Abdulsadda et al. 2011 [35] | Micromachining | IPMC | Localization accuracy at the source-sensor separation of 1 body length |
4. Hydrodynamic environment sensing and vortices detection

Due to the limitations of existing measurements methods in complex natural flows and the emergence of the above mentioned various types of sensors, scientists have started to use ALL systems consisting of these sensors to obtain information from fluid environment. Efforts are devoted into the following fields: flow field characteristics identification, flow velocity and direction detection, vortex street properties detection. Carriers boarded with ALL mentioned in this section are shown in Figure 11.

4.1. Flow field characteristics identification

In 2013, Kruusmaa et al. presented that the robotic fish boarded with 5 pressure sensors (Figure 11(b)) was able to identify the flow regimens (uniform flow and periodic turbulence)
Figure 11: Different carriers boarded with ALL mentioned in Section 4. (a) A schematic diagram of the sensor platform used in [50]. (b) CAD view of the robot used in [51]: 1, rigid head of the robot; 2, servo-motor; 3, middle part for holding the head and the tail; 4, steel cables; 5, actuation plate; 6, compliant tail; 7, rigid fin; S1-S5, pressure sensors. (c) Location of the 16 pressure sensors and 2 accelerometers in the ALL Probe used in [52]. (d) Illustration of the lateral line probe used for field measurements showing shape and sensor distribution in [53]. (e) A 3-D model of the carrier in [54].
according to the pressure around the underwater vehicle in 2013 [51].

In 2018, they used the ALL probe consisting of 11 piezoresistive pressure sensors (Figure 11(d)) to capture hydrodynamic information. The probe provided an average flow velocity in turbulent flows which was comparable to the results measured practically. According to the characteristics of the fluid, the flows were classified by comparing the probability distribution of turbulent pressure fluctuation [53].

Liu et al. also made great contribution in flow field characteristics identification. In 2019, they proposed an improved pressure distribution model to calculated the pressure around the ALL which consisting of 23 pressure sensors (Figure 11(e)) and then established a visualized pressure difference matrix to identify flow field in different conditions. A four-layer convolutional neural network model was constructed to evaluate the accuracy of this method [54].

4.2. Flow velocity and direction detection

In 2013, Kruusmaa et al. proved that the flow speed can be estimated only by the average pressure on the sides of the robotic fish (Figure 11(b)). They put forward a fitted formula representing the relationship between the average pressure drop and the flow speed based on Bernoulli formula. Besides, they also reported that the flow direction could be detected because that the pressure on the side which the probe turned towards the flow was higher [51].

In the same group, they presented a new way for flow speed estimation with the help of ALL probe consisting of 10 piezoresistive pressure sensors (Figure 11(c)) without sensor calibration in 2015, which is of great convenience. Induced by the interactions between fluid and the robot body, fluctuations in the pressure field around the body could be detected by the ALL probe. Based on Bernoulli formula likewise, they introduced a semiempirical resampling process. Compared with results measured by an acoustic Doppler velocimeter in a vertical slot fishway, the accuracy of this method was validated [52].

Besides, Tuhtan et al. made great progress in natural flow measurements using an ALL probe combined with signal processing methods in 2016. The probe is the same as showed in Figure 11(c). They proved that information acquired by the probe was transformed into two important hydrodynamic primitives, bulk flow velocity and bulk flow angle via canonical signal transformation and kernel ridge regression. Moreover, they showed that this method was effective not only when the sensor was parallel to the flow, but also in the condition that the angular deviation was large. While used in a natural river environment, the method had an error of 14 cm/s [55]. In 2016, they presented a new method to estimate the flow velocity ranging from 0 to 1.5 m/s. They collected time-averaged flow velocity and pressure acquired by the ALL in highly turbulent flow and put forward a signal processing approach combining Pearson product-moment correlation coefficient features and artificial neural network [56]. This method is potential to interpret the underwater preferences of fish in real environment.

Additionally, Liu et al. in 2020, based on a fitting method and a back propagation neural network model, successfully predicted the flow velocity and direction and the moving velocity [57]. This progress provided another possibility to identify hydrodynamic information for
4.3. Vortex street properties detection

In 2006, Yang et al. used ALL system to study the spatial velocity distribution of Kármán vortex street and visualized the velocity distribution of Kármán vortex street generated by a cylinder for the first time [46].

Ren et al. theoretically studied the perception of vortex streets using real lateral line in 2010. Based on potential flow theory, they constructed the model of flow field around the fish, and then explained how the fish captured the characteristics of vortices with the help of lateral line CNs. The model were applied to estimate the range of the vortex, transmission speed, direction, distance between the vortex streets and distance between the fish and vortex street [58].

Klein et al. used an artificial canal equipped with optical flow sensors which have been presented in section 2 (Figure 9(a)). They have demonstrated the capability of the ALL canals to detect the vibrating sphere. Additionally, vortices generated by an upstream cylinder were also detected. Based on the hydrodynamic information acquired by the ALL canal, they succeeded in calculating the flow velocity and the size of the cylinder [41].

In 2012, Venturelli et al. used digital particle image velocimeter to visualize the flow state and a rigid body equipped with 20 pressure sensors (Figure 11(a)) parallel distributed to acquire flow field information and then applied time and frequency domain methods to describe hydrodynamic scenarios in steady and unsteady flows respectively. The array of pressure sensors showed a capability of discriminating vortex streets from steady flows and detecting the position and direction of the body relative to the incoming flow. A series of hydrodynamic parameters were also calculated, such as vortex shedding frequency, vortex travelling speed and downstream distance between vortices [50].

Free et al. presented a method to estimate the parameters of vortices in 2017. They used a straight array of 4 pressure sensors for a spiral vortex and a square array for a Kármán vortex street. Based on potential flow theory and Bernoulli principle, the measurement equation was incorporated in a recursive Bayesian filter, as a consequence of which, the position and strength of vortices have been successfully estimated. Moreover, they identified an optimal path for underwater vehicles to swim through a Kármán vortex street using empirical observability. Experiments demonstrated the effectiveness of the closed-loop control [59]. Based on the results above, in 2018, they installed the array on a Joukowski foil and detected Kármán vortex streets nearby. With the help of trajectory-tracking feedback control, the robotic foil performed fish-like slaloming behavior in a Kármán vortex street [60].

In this section, we have focused on the application of ALL system in detecting flow characteristics. Table 3 as follows lists different projects mentioned above and related ongoing studies. Existing results are mainly based on static ALL sensors and experiments are conducted in laboratory environment. The characteristics of flow which can be detected are also limited. For further study, with the improvement of ALL system, we can pay more...
attention to natural environment experiments, where the complexity of the water environment and the complex movements of the robot fish make it more difficult for perception.

Table 3: Classification of existing studies in hydrodynamic environment sensing and vortices detection

| Project                              | Author                     | ALL Sensors                                                                 | Laboratory experiment/ Natural environment experiment |
|--------------------------------------|----------------------------|----------------------------------------------------------------------------|------------------------------------------------------|
| Flow field characteristics identification | Kruusmaa et al. 2013 [51] | 5 pressure sensors (Intersema MS5407-AM)                                  | Laboratory experiment                                 |
|                                      | Kruusmaa et al. 2018 [53] | 11 pressure sensors (SM5420C-030-A-P-S)                                   | Laboratory experiment                                 |
|                                      | Liu et al. 2019 [54]      | 23 pressure sensors (MS5803-07BA)                                         | Laboratory experiment                                 |
| Flow velocity and direction detection | Kruusmaa et al. 2013 [51] | 5 pressure sensors (Intersema MS5407-AM)                                  | Laboratory experiment                                 |
|                                      | Kruusmaa et al. 2015 [52] | 16 pressure sensors (SM5420C-030-A-P-S)                                   | Laboratory experiment                                 |
|                                      | Kruusmaa et al. 2016 [56] | 16 pressure sensors (SM5420C-030-A-P-S) and 2 three-axis accelerometers (ADXL325BCPZ) | Laboratory experiment and natural environment experiment |
|                                      | Liu et al. 2020 [57]      | 23 pressure sensors (MS5803-07BA)                                         | Laboratory experiment                                 |
| Vortex street properties detection    | Yang et al. 2006 [46]     | 16 HWA sensors                                                             | Laboratory experiment                                 |
|                                      | Ren et al. 2010 [58]      |                                                                            | Theoretical model                                     |
|                                      | Klein et al. 2011 [41]    | Optical sensors                                                            | Laboratory experiment                                 |
|                                      | Venturelli et al. 2012 [50]| 20 pressure sensors                                                         | Laboratory experiment                                 |
|                                      | Kruusmaa et al. 2013 [51] | 5 pressure sensors (Intersema MS5407-AM)                                  | Laboratory experiment                                 |
|                                      | Free et al. 2017 [59]     | An array of 4 pressure sensors                                             | Laboratory experiment                                 |
|                                      | Free et al. 2018 [60]     |                                                                            | Laboratory experiment                                 |
5. ALL based dipole source detection

The localization ability of underwater objects with the help of ALL system can effectively improve the viability of robotic fish in underwater environment. In addition to the anti-Kármán vortex street, a near-dipole flow field is generated by the fin while fish swims. This can also explain how predators capture preys [61]. Dipole oscillation source detection has become a common problem in hydrodynamics and the development of ALL. While the dipoles are vibrating or moving in a certain way, the pressure and the flow speed will change accordingly. By measuring these information with the help of ALL, we can infer the motion of the object for further study. Carriers boarded with ALL mentioned in this section are shown in Figure 12.

Tang et al. represented an array of 8 pressure sensors installed on the surface of an underwater vehicle (Figure 12(a)) inspired by lateral line for near-field detection in 2019. The pressure field generated by vibrating sphere which was simulated as an underwater pressure source was derived by means of linearizing the kinematic and dynamic conditions of the free surface wave equation. The fish-shaped structure they used was boarded with 8 pressure sensors. The pressure field detected by the ALL was fit with simulation results [62].

In 2007, Yang et al. used an array of AHCs (Figure 12(b)) whose sensory unit has been introduced in section 2 (Figure 6(b)) to locate and track the dipole source. As for mapping the pressure field produced by the dipole source, the array performed well and the results was consistent in experiments and theory. As for tracking the trail, a cylinder was put in a steady flow with the speed of 0.2 m/s to simulate the hydrodynamic trail which was dominated by Kármán vortex street consequently [30].

In 2010, the same group developed an ALL by wrapping 15 pressure sensor around a cylinder (Figure 12(c)) to mimic real fish and proved its localization capability. They used a beamforming algorithm to image hydrodynamic events in a 3-D domain. Consequently, the ALL sensors was demonstrated to be able to localize a dipole source and a tail-flicking crayfish accurately in varieties of conditions [32].

Additionally, Asadnia et al. packaged Pb(Zr_{0.52}Ti_{0.48})O_3 thin-film piezoelectric pressure sensors for underwater sensing in 2013. The array of 2 by 5 sensor has been showed in section 2 (Figure 7(a)). While the dipole was driven at the frequency of 15 Hz and moved parallel to the array, by measuring the maximum peak-to-peak output of the sensors, they approximately estimated the position of the dipole source. To detect the flow velocity generated by the dipole source, the array showed a resolution of 3 mm/s [33].

Abdulsadda et al. put forward an array of ALL sensors based on the sensing capability of IPMC in 2011. The signals were processed through a widely-used neural network, which was similar to the biological counterpart. The ALL has been presented in the section 2 as well (Figure 7(c)). Experiments proved that the ALL could effectively locate the dipole source and the flapping tail. Moreover, the more sensors was used, the more precise the results were [35]. In 2013, based on an analytical model of flow field produced by the dipole source, they presented another two schemes, Gauss Newton (GN) algorithms which were used to solve the nonlinear estimation problem by means of linear iteration and Newton Raphson (NR)
Figure 12: Different carriers boarded with ALL mentioned in Section 5. (a) The fish-shaped prototype inspired by the trout lateral line in [62]. (b) Photo of an AHC sensor array used in [30]. (c) Diagram of the ALL showing the biomimetic neuromast layout in [32]. (d) The design of ALL in [63]. (e) The design of ALL in [64]. (f) An experimental prototype of IPMC-based lateral line system used in [65]. (g) A prototype of an ALL with sensors used in [66]. (h) Robotic fish with the PVDF sensor along with the oscillating sphere in [67]. (i) Sensor layout and lateral line carrier physical map in [68].
algorithms which were used to solve the nonlinear equation under the condition of first-order optimality, to locate the dipole source and estimate amplitude and direction of the vibration. Additionally, they improved the design of intra-sensor spacing (Figure 12(f)) of the lateral line by analysis based on Cramer-Rao bound (CRB). With 19 dipole sources placed along an ellipsoidal track, the simulation and experiment results both proved the accuracy of this model [65] [69] [70]. In order to reduce the influence of uncertainty in measurements and flow model and thus identify a vibrating dipole accurately, Tan et al. developed a specialized bi-level optimization methodology to optimize the design parameters of the ALL [66] (Figure 12(g)).

In the aspect of using hot-wire flow sensors to detect the dipole source, Pandya et al. made great contributions in 2006. Section 2 has introduced the hot-wire ALL developed by them (Figure 10(a)). To make full use of the ALL, they reported on the implementation of a algorithm consisting of template training approach and the modeling approach based on minimum mean-squared error (MMSE) algorithm in order to locate and track a vibrational dipole source [44].

In 2010, by detecting the parallel and the perpendicular velocity components, Dagamseh et al. used an array of hair flow sensors to reconstruct the velocity field induced by the dipole source in the air and measure the distance [71] [72] [73] [74]. In 2013, they employed beamforming techniques and improved the performance of the sensor array [75].

Inspired by the sensory abilities of lateral line, Zheng et al. developed an ALL composed of 9 underwater pressure sensors forming a cross (Figure 12(d)) to locate a dipole source in 2018. For the sake of handling nonlinear pattern identification problem, they adopted the method of generalized regression neural network which performed well on condition that the array is below 13cm away from the dipole source [63]. Besides, the same group develop another ALL composed of 9 pressure sensors in a straight line (Figure 12(e)) to locate the dipole source. Lin et al. modelled the pressure field of the dipole source and obtained the position through least square method by means of the information acquired by the pressure sensors [64]. Ji et al. employed the same ALL and put forward a new method named MUSIC (multiple signal classification) for the purpose of locating dipole source with high-resolution based on spatial spectrum estimation. Moreover, they also presented a MVDR (minimum variance distortionless response) method which improved the previous Capon’s method (an adaptive beamforming-based method). For further study, MUSIC method showed a potential to locate two close dipole sources [76]. In 2019, Ji et al. established a quantitative and method-independent Cramer-Rao lower bound (CRLB) model to evaluate the localization performance of the above two methods, least square and MUSIC, which provided guidance on the optimal design of the ALL with the least sensors and the most appropriate spacing [77].

In 2018, Liu et al. developed an ALL consisting of 25 high precision pressure sensors (Figure 12(i)). They established a mathematical model of the dipole source through Euler equation and plane potential flow theory to describe the relationship between the characteristic parameters of source and the surface pressure of the underwater vehicle and successfully detected the position, frequency and amplitude of the source through a neural network model. The consistency of simulation and experiment results demonstrated the effectiveness of the
In 2018, Yen et al. adopted the potential flow theory to predict the hydrodynamic pressure and presented a method to follow periodic stimuli generated by an oscillating source. The fin of the robot was regarded as an oscillator. By subtracting the pressure induced by the robotic fish from the pressure measured by the PVDF sensor (Figure 12(h)), they acquired the pressure generated by the source. Based on this, the robotic fish was able to adjust the amplitude, frequency, offset according to the phase difference [67]. Furthermore, this method lays a solid foundation for controlling the robotic fish to swim in a school.

In 2019, Wolf et al. used a 2-D array of 8 all-optical sensors to measure the velocity profiles of a underwater object and then adopted feed-forward neural network and recurrent neural network to reconstruct the position of the object [78] [79]. Furthermore, they implemented near field object classification based on hydrodynamic information with an Extreme Learning Machine neural network. This method provided more information about the shape comparing to other 2-D sensing array [80].

In this section, we have put emphasis on discussing applications of ALL in locating and tracking the dipole source, especially the difference in approaches to reaching the results. Table 4 as follows can be a summary of this section. Flow induced by oscillating sources is only one of the most basic forms of water flows and similar to wake flow generated by real fish. Based on the results above, we can also conduct natural environment experiments in which ALL is installed on robotic fish to follow real fish, even fish school and locate them in real time.

| Author            | ALL Sensors                          | Approaches                                         |
|-------------------|--------------------------------------|----------------------------------------------------|
| Tang et al. 2019 [62] | 8 eight pressure sensors             | Linearizing the kinematic and dynamic conditions of the free surface wave equation |
| Yang et al. 2007 [30]  | An array of AHC sensors              | Measuring the maximum peak-to-peak output of the sensors |
| Yang et al. 2010 [32]  | 15 biomimetic neuromasts             | Beamforming algorithm                               |
| Pandya et al. 2006 [44] | an array of 16 hot-wire anemometers | Template training approach and the modeling approach |
| Asadnia et al. 2013 [33] | An array of 2 by 5 pressure sensors | Maximum pressure signal                            |
| Abdulsadda et al. 2011 [35] | 5 IPMC sensors                       | Neural network                                      |
| Authors                     | Sensors Description                              | Algorithms/Methods                      |
|----------------------------|-------------------------------------------------|----------------------------------------|
| Abdulsadda et al. 2013 [65]| 6 IPMC sensors                                   | Gauss Newton and Newton Raphson algorithms |
| Abdulsadda et al. 2012 [69] [70]|                                      |                                        |
| Ali Ahrari et al. 2016 [66]| Multiple flow velocity sensors                  | Bi-level optimization methodology      |
| Zheng et al. 2018 [63]    | 9 underwater pressure sensors forming a cross   | Generalized regression neural network   |
| Lin et al. 2018 [64]      | 9 pressure sensors in a straight line           | Least square method                    |
| Ji et al. 2018 [76]       |                                                 | MUSIC, MVDR                            |
| Ji et al. 2019 [77]       |                                                 | CRLB model                             |
| Liu et al. 2018 [68]      | 25 high precision pressure sensors              | Euler equation, plane potential flow theory and neural network |
| Yen et al. 2018 [67]      | a PVDF sensor                                   | Potential flow theory                  |
| Dagamseh et al. 2009 [71] [72]| an array of hair flow-sensors                  | Detecting the parallel and the perpendicular velocity components, beamforming techniques |
| Dagamseh et al. 2010 [73] [74]|                                      |                                        |
| Dagamseh et al. 2013 [75]|                                      |                                        |
| Wolf et al. 2019 [78] [79]| 8 all-optical flow sensors                      | Feed-forward neural network and recurrent neural network |
| Wolf et al. 2020 [80]     |                                      |                                        |

### 6. Flow-aided control of underwater robots using ALL system

Lateral line plays an important part in sensing flow for fish school, which has inspired scientists worldwide to devote to developing underwater vehicles boarded with ALL system consisting of an array of sensors. The precious sections mainly presented applications based on a static ALL. If the ALL is moving like fish, the sensing difficulty will greatly increase. Assisted by ALL sensors, underwater vehicles are in a position to obtain fluid information accurately and effectively, providing the possibility to implement vehicles motion pattern identification and autonomous control. Varieties of experiments have been carried out in this domain, such as pattern identification, motion parameters (speed and direction) estimation and control, localization, obstacles detection and avoidance, energy consumption reduction and
neighborhood robotic fish perception. Carriers boarded with ALL mentioned in this section are shown in Figure 13.

Figure 13: Different carriers boarded with ALL mentioned in this Section 6. (a) The robotic fish prototype in [81]. (b) The mechanical structure and electronics of the robotic fish used in [82]. (c) Illustration of reference frames I and O. TE denotes the trailing edge and LE the leading edge in [83]. (d) Modular design of robotic foil in [84]. An array of eight IPMC sensors are installed below an array of pressure sensors. (e) Conceptual 3-D drawing of the vehicle in [85]. (f) Photographs of the robotic fish in [86].

In 2013, Akanyeti et al. firstly dived into the problem of hydrodynamic sensing on condition that the ALL is moving. Based on Bernoulli equation, they presented a formula about pressure detected by the ALL and the moving velocity and acceleration, which laid a solid foundation for the following study [87]. Additionally, Chambers et al. made a study of using a vertically or horizontally moving ALL to sense local flow. They came to
a conclusion that a moving ALL performed better than static [88]. For further studies, a moving carrier boarded with ALL which has a great sensing ability can provide more valuable experimental data. The project FILOSE using a robotic fish showed in Figure 11(b) not only aimed to study how fish perceive and respond to fluid simulation, but also constructed a bioinspired robot on the basis of it. Boarded with ALL sensors, robotic fish measured the data from surrounding fluid environment which provided information on hydrodynamic features. And then by analysis, the relationship between fluid data and kinestate of robotic fish was established, showing a new idea of robotic fish self-control. Several experiments have been conducted as follows: 1) detecting direction while swimming against the flow, 2) swimming along a predetermined trajectory, 3) maintaining stable position in constant current, 4) reducing energy consumption in turbulence, 5) reducing energy consumption by maintaining a stable position in the hydrodynamic shadow, 6) conducting control-experiments between real fish and robotic fish [89]. In this section, we will introduce flow-aided control of underwater robots using ALL system by category.

6.1. Pattern identification

In 2020, Zheng et al. made a breakthrough in motion parameters estimation of a robotic fish boarded with 11 pressure sensors (MS5803-01BA) (Figure 13(a)). When the robotic fish moved at a specific state, such as rectilinear motion, turning motion, gliding motion, and spiral motion, they established a model combining the motion parameter including linear velocity, angular velocity, motion radius, etc. and the superficial hydrodynamic pressure variations. Robotic fish acquired the motion parameters based on the pressure detected by the ALL and then predicted the trajectory [90]. This work is of great importance for future study on self-trajectory-control.

In 2014, Liu et al. conducted experiments that robotic fish (Figure 13(b)) sense pressure information while swimming in different gaits such as forward swimming, turning, ascending and diving. And then based on feature points extracted from the data, they adopted a subtractive clustering algorithm to recognize the swimming gaits of robotic fish [91]. The success of this approach lays a solid foundation for quick control of robotic fish.

6.2. Motion parameters (speed and direction) estimation and control

In regard to the control of robotic fish, there have been a large number of results as well. Instantly, Kruusmaa et al. implemented rheotaxis behaviour in robotic fish in 2011. With the pressure sensors detecting flow information, they put forward a linear control law which helped the robotic fish to adjust the beat frequency in order to maintain position in the steady flow [92]. In 2013, they used a 50cm-long robotic fish (Figure 11(b)) mimicking the geometry and swimming mode of a rainbow trout and put forward a formula for estimating the speed. The experiments have proved the validity of it [51]. Inspired by the Braitenberg vehicle 2b, they installed two pressure sensors on both sides of the head which could detect the pressure difference on the left and right side of the robotic fish [93]. And then it was able to change the direction of swimming according to the difference to remain stable. Ulteriorly, they realized
Fish lateral line inspired perception and flow-aided control: A review

the position estimation and position stability of the robotic fish in steady water flows and behind solid objects [51].

Additionally, Xie et al. designed a robotic fish inspired by the geometry and swimming pattern of an ostraciiform boxfish shown in Figure 13(b). The robotic fish is boarded with an ALL composed of an array of 11 pressure sensors (Consensic CPS131) and an inertial measurement unit (IMU). The former is used for fluid dynamic pressure data acquisition while the latter is used to monitor the robot pitch, yaw and roll angles. In order to reduce errors on account of sensors’ inaccuracy and instability, they employed an optimal information fusion decentralized filter in 2015, as a consequence of which, the accuracy of speed estimation has been greatly improved. The speed estimation formula is derived from Bernoulli principle and corrected by local filter from ALL and IMU [82]. Furthermore, in 2016, they put forward a nonlinear prediction model including distributed pressure and angular velocity to estimate the speed of robotic fish [94].

Moreover, Paley et al. also presented something new in flow speed and angle-of-attack detecting in 2015. They used a new type of flexible robotic fish whose shape is Joukowski-airfoil (Figure 13(c)) with distributed pressure sensors. Flow speed, angle-of-attack, and foil surfaces were estimated by a recursive Bayesian filter assimilation pressure measurement. And they combined an inverse-mapping feedforward controller based on an average model derived for periodic actuation of angle-of-attack and a proportional-integral feedback controller utilizing the estimated flow information to implement the closed-loop speed-control strategy [84] [83] [95].

6.3. Obstacles detection and avoidance

Furthermore, extensive efforts have been done in obstacle detection and avoidance. Inspired by sensitivity of lateral line to the presence of oncoming currents and walls or obstacles, Paley et al. developed a kind of wing underwater vehicle boarded with ALL sensors in 2015 (Figure 13(d)). Employing potential flow theory, they simulated the flow field around vehicle in the situation that the flow was uniform and there were obstacle upstream. A nonlinear estimation model of free stream flow speed, attack of angle and relative position of obstacles by measuring local flow speed and pressure difference was derived theoretically. In order to implement the stability of swimming direction and position behind obstacles, they presented a recursive Bayesian filter. Finally, they discussed the Closed-loop control strategy ulteriorly [84].

In addition, Martiny et al. studied intensively in obstacles detection and avoidance in 2009. They developed an autonomous underwater vehicle equipped with 4 ALL sensors (Figure 13(e)). Using hot-wire anemometry, it measured local flow speed around the vehicle, which was proved related to the distance between obstacles and the vehicle theoretically and experimentally [85].

Yen et al. have made a breakthrough in obstacles detection and navigation in 2017. They used a robotic fish boarded with 3 ALL sensors (Figure 13(f)) to measure nearby pressure variations, on the basis of which, they presented a way to control a robotic fish to swim along
a straight wall. In theory, the tail of the robotic fish was regarded as an oscillating dipole in a 2-D potential flow approximately and the wall effect was described by an image dipole on the opposite side of the wall. The robotic fish responded to the pressure variations in order to keep a fixed distance from the wall. A qualitative relationship between velocity and wall effect was concluded in this research [86].

6.4. Neighborhood robotic fish perception

Not only have there been various results with respect to a single robotic fish, large amounts of experiments have also been carried out in multi-body control. Lots of work in this research field has been done by Xie et al. In 2015, they came to the conclusion by experiments that robotic fish (Figure 13(b)) was capable of sensing the beating frequency of the robot swimming in front and the distance between the two robots with the help of ALL system [96]. In 2017, they used the ALL system to detect the reverse Kármán-vortex street-like vortex wake generated by its adjacent robotic fish. By extracting meaningful information from the pressure variations caused by the reverse Kármán-vortex street-like vortex wake, the oscillating frequency/amplitude/offset of the adjacent robotic fish, the relative vertical distance and the relative yaw/pitch/roll angle between the robotic fish and its neighbor were sensed efficiently [97]. This progress lays a solid foundation for multi-body interactions research in the future.

In 2019, Zheng et al. used a robotic fish which is shown in Figure 13(a) to conduct neighborhood perception experiments. Firstly, based on Bernoulli principles, they established a theoretical model to describe the hydrodynamic pressure variations on the surface of two adjacent robotic fish which swam diagonally ahead another [81]. Then, they utilized dye injection technique, hydrogen bubble technique and computational fluid dynamics simulation to study the vortices induced by the robotic fish separation. Besides, on the basis of the previous model, they also presented the relationship describing longitudinal separations and superficial hydrodynamic pressure variations of two robotic fish [98]. This progress provided a new method for robotic fish school sensing.

In addition to the results mentioned above, some other applications of ALL in robotic fish control are introduced below. With respect to localization, Muhammad et al. produced preliminary results by flow feature extraction and comparison of compact flow features, based on which they developed an underwater landmark recognition technique in 2015 [99]. This technique enables robotic fish to recognize locations that it has previously visited both in semi-natural and natural environments. In 2017, Francisco et al. proposed a map-based localization technique that employd simulated hydrodynamic maps. They used a computational fluid dynamics model to generate a flow rate diagram. Hydrodynamic information was acquired by ALL systems and analyzed to estimate the speed. Compared with the flow rate diagram, the location of the robotic fish was found out in the flow rate maps which was simulated from hydrodynamic results [100].

As for energy consumption, Kruusmaa et al. conducted a control experiment that
the robotic fish swims in steady flow, behind a cylinder and behind a cuboid in 2013. Consequently, swimming behind a cuboid consumed the least energy. They assumed that this phenomenon was on account of the presence of the well-defined suction zone behind the cylinder. Both obstacles avoidance and energy consumption reduction are of giant significance to the navigation of robotic fish [51].

In this section, we have focused on the application of ALL system in robotic fish control. Table 5 as follows lists different projects mentioned above and related ongoing studies. Similar to the previous sections, robotic fish in this section is mostly static or move in a simple state, such as rectilinear motion and turning motion in laboratory environment. However, the motion of real fish and the real underwater environment are much more complicated, which makes it more difficult for underwater sensing. To solve these problems, we need to improve the sensing system and establish new control algorithms for natural environment studies. Additionally, perception of underwater obstacles provides a new approach for underwater environment reconstruction and results of neighborhood robotic fish perception can be a basis of control of multi robotic fish, both of which are potential to promote underwater exploration.

| Project                          | Author                      | ALL Sensors                                             | Laboratory experiment/ Natural environment experiment |
|----------------------------------|-----------------------------|---------------------------------------------------------|------------------------------------------------------|
| **Pattern identification**       | Liu el al. 2014 [91]        | 9 pressure sensors (CPS131)                             | Laboratory experiment                                |
|                                  | Zheng et al. 2020 [90]      | 11 pressure sensors (MS5803-14BA)                       | Laboratory experiment                                |
| **Direction detection and holding** | Kruusmaa et al. 2012 [93]  | 5 pressure sensors (Intersema MS5407-AM)               | Laboratory experiment                                |
|                                  | Kruusmaa et al. 2013 [51]  |                                                         |                                                      |
|                                  | Paley et al. 2013 [95]      | 8 IPMC sensors and four embedded pressure sensors [84]/ six pressure sensors [83] | Laboratory experiment                                |
|                                  | Paley et al. 2015 [84] [83] | (Servoflo MS5401-BM) [83]/ The sensors (MikroTip Catheter Pressure Transducers) [95] |                                                      |
| **Speed estimation**             | Kruusmaa et al. 2013 [51]  | 5 pressure sensors (Intersema MS5407-AM)               | Laboratory experiment                                |
|                                  | Xie et al. 2015 [82]        | 11 pressure sensors (Consensic CPS131)                 | Laboratory experiment                                |
|                                  | Xie et al. 2016 [94]        |                                                         |                                                      |
7. Discussion

In the previous sections, we have reviewed ALL sensors based on different principles and applications in flow field characteristics identification, dipole source detection and control of underwater robots. Although fish lateral line provides inspiration for the design of ALL sensors and underwater detection, it also serves as a strict standard for research. There have been great progress in this area, however, performance of existing ALL system is still quite far from that of real fish.

ALL sensors which have been developed are no match for that of real fish through evolution in sensitivity, stability, coordination and information processing. We can optimize
the design of the sensitive element and consider the resonance frequency for a better perception of ALL sensors. As for the stability, measurement errors in different temperature or pressure conditions should be taken into account. Additionally, waterproofing measures is necessary for the normal operation of sensors in the harsh conditions underwater. The development of new materials and micromachining technology provides possible methods for improvements in both areas. Not only should the performance of a single sensory unit be improved, the coordination of an array of ALL sensors is also important. Existing arrays of ALL sensors are mainly composed of a single type of sensors (pressure sensors or flow sensors) and arranged regularly, which is quite from that of real fish. Real lateral line consists of SNs and CNs for a comprehensive perception of surrounding environment and sensing cells are distributed in a specific pattern for a better sensing. Using pressure sensors and flow sensors simultaneously is a potential method to optimize the array of ALL sensors. Besides, we can put forward evaluation indexes of ALL in order to find out the best placement of sensors on the surface of underwater robots. In terms of information processing, the fish lateral line has many different sensory functions, which can be a reference standard for ALL sensors. Many algorithms in velocity measurements and dipole source detection have been put forward, but the sensory ability of ALL does not stop here. ALL has the potential to sense the obstacles, fish schools and even reconstruct the surrounding water environment, which is a basis of follow-up research on control of underwater robots.

As for hydrodynamic characteristics identification, there have been many results based on ALL system. However, existing results are mainly based on laboratory experiments where the motion of ALL carrier is simple such as static state and rectilinear motion and the water environment is stable. By contrast, the motion of real fish and underwater environment are much more complicated, which will greatly increase the difficulty of experiments. With the development of ALL sensors, natural experiments are necessary for complete imitation of real fish lateral line.

In dipole source detection, many methods and algorithms have been presented because oscillatory flow is one of the most basic flows and can be used to simulate the wake produced by the wagging tail of fish, which is important for further study on location and track of real fish. But the matching degree of oscillating flow and fish wake needs further exploration. On the basis of it, more experiments on real-time location of fish school and mimicking the group behavior of fish may become a focus in the future.

Flow-aided control of underwater robots is a promising project which has a wide range of applications in marine exploration. The first priority is to establish the motion model of underwater robots based on hydrodynamics theory or date-driven methods which provides a way for self-identification of motion pattern in the conditions where it is impossible to observe. Establishment of model can be a theoretical instruction for control strategies. In addition, obstacles recognition and avoidance is another necessary ability for autonomous control. Based on the location of obstacles, robots is potential to reconstruct the surrounding environment and plan an optimal path for navigation. Except for a single robotic fish, perception and control of a robotic fish group may greatly improve the efficiency of underwater exploration and the success rate of underwater missions with the help of ALL.
8. Conclusion

In this article, we briefly introduced the morphology and mechanism of the lateral line for a further understanding. And then we put emphasis on discussing progress in biomimetics inspired by lateral line. Different kinds of sensors based on different principles have been explored, which provides a new approach for fluid information detection. Furthermore, scientists have arranged sensors to fabricate ALL system on underwater vehicle bodies to assist in underwater detection, which is superior to traditional methods in applicability and flexibility. For hydrodynamic environment sensing and characteristic detection, we have made great progress in flow field characteristics identification, flow velocity and direction detection, vortex street properties detection. Additionally, various algorithms have been put forward to locate the dipole source. Recently, ALL system have been used for the autonomous control of underwater robotic fish.

In future, based on existing results, we need to develop sensor units demonstrating higher sensitivity and optimize the distribution of ALL on the robotic fish surface. Combining a high-performance sensor array with a more efficient signal processing algorithm, robotic fish is potential to show a sensory ability close to real fish, which is a foundation for natural environment experiments in the following studies. It is necessary to present new universal control algorithms for the autonomous control of robotic fish based on ALL systems. Perception of underwater obstacles provides a new approach for underwater environment reconstruction, which is important for underwater location and navigation. Moreover, application of ALL in the control of robotic fish school will also become a focus issue, which is important in multi-robot interaction and cooperation for future ocean exploration. With the development of new materials, fabrication technology and artificial intelligence, the performance of ALL system will be comparable to that of real fish.

The development of ALL systems provides a powerful tool for ocean exploration. Although great efforts have been devoted in this area, there is a long way to go to realize the comparable sensory ability and autonomous control of robotic fish to real fish.

Acknowledgments

This work was supported in part by grants from the National Natural Science Foundation of China (NSFC, No. 91648120, 61633002, 51575005) and the Beijing Natural Science Foundation (No. 4192026).

Reference

[1] Michael S Triantafyllou and George S Triantafyllou. An efficient swimming machine. *Scientific american*, 272(3):64–70, 1995.

[2] Junzhi Yu, Lizhong Liu, Long Wang, Min Tan, and De Xu. Turning control of a multilink biomimetic robotic fish. *IEEE Transactions on Robotics*, 24(1):201–206, 2008.
Fish lateral line inspired perception and flow-aided control: A review

[3] Jianhong Liang, Tianmiao Wang, and Li Wen. Development of a two-joint robotic fish for real-world exploration. *Journal of Field Robotics*, 28(1):70–79, 2011.

[4] Wei Wang and Guangming Xie. Online high-precision probabilistic localization of robotic fish using visual and inertial cues. *IEEE Transactions on Industrial Electronics*, 62(2):1113–1124, 2014.

[5] Junzhi Yu, Ming Wang, Min Tan, and Jianwei Zhang. Three-dimensional swimming. *IEEE robotics & automation magazine*, 18(4):47–58, 2011.

[6] Alessandro Crespi, Daisy Lachat, Ariane Pasquier, and Auke Jan Ijspeert. Controlling swimming and crawling in a fish robot using a central pattern generator. *Autonomous Robots*, 25(1-2):3–13, 2008.

[7] Keehong Seo, Soon-Jo Chung, and Jean-Jacques E Slotine. Cpg-based control of a turtle-like underwater vehicle. *Autonomous Robots*, 28(3):247–269, 2010.

[8] Auke Jan Ijspeert, Alessandro Crespi, Dimitri Ryczko, and Jean-Marie Cabelguen. From swimming to walking with a salamander robot driven by a spinal cord model. *science*, 315(5817):1416–1420, 2007.

[9] Joachim Mogdans and Horst Bleckmann. Coping with flow: behavior, neurophysiology and modeling of the fish lateral line system. *Biological cybernetics*, 106(11-12):627–642, 2012.

[10] R Glenn Northcutt. The phylogenetic distribution and innervation of cranian mechanoreceptive lateral lines. In *The mechanosensory lateral line*, pages 17–78. Springer, 1989.

[11] Karen P Maruska. Morphology of the mechanosensory lateral line system in elasmobranch fishes: ecological and behavioral considerations. *Environmental Biology of Fishes*, 60(1-3):47–75, 2001.

[12] Guijie Liu, Anyi Wang, Xinbao Wang, and Peng Liu. A review of artificial lateral line in sensor fabrication and bionic applications for robot fish. *Applied bionics and biomechanics*, 2016, 2016.

[13] Sheryl Coombs, John Janssen, and Jacqueline F Webb. Diversity of lateral line systems: evolutionary and functional considerations. In *Sensory biology of aquatic animals*, pages 553–593. Springer, 1988.

[14] Heinrich Münz. Morphology and innervation of the lateral line system in sarotherodon niloticus (l.) (cichlidae, teleostei). *Zoomorphologie*, 93(1):73–86, 1979.

[15] Tan Shizhe. Underwater artificial lateral line flow sensors. *Microsystem technologies*, 20(12):2123–2136, 2014.

[16] Sietse M van Netten. Hydrodynamic detection by cupulae in a lateral line canal: functional relations between physics and physiology. *Biological cybernetics*, 94(1):67–85, 2006.

[17] Matthew J McHenry, James A Strother, and Sietse M Van Netten. Mechanical filtering by the boundary layer and fluid–structure interaction in the superficial neuromast of the fish lateral line system. *Journal of Comparative Physiology A*, 194(9):795, 2008.

[18] Zhifang Fan, Jack Chen, Jun Zou, David Bullen, Chang Liu, and Fred Delcomyn. Design and fabrication of artificial lateral line flow sensors. *Journal of Micromechanics & Microengineering*, 12(5):655–661.

[19] Nannan Chen, Craig Tucker, Jonathan M. Engel, Yingchen Yang, and Liu Chang. Design and characterization of artificial haircell sensor for flow sensing with ultrahigh velocity and angular sensitivity. *Journal of Microelectromechanical Systems*, 16(5):999–1014, 2007.

[20] Michael E Mcconney, Nannan Chen, David Lu, Huan A Hu, Sheryl Coombs, Chang Liu, and Vladimir V Tsukruk. Biologically inspired design of hydrogel-capped hair sensors for enhanced underwater flow detection. *Soft Matter*, 5(2):292–295, 2009.

[21] A. Qualtieri, F. Rizzi, M.T. Todaro, A. Passaseo, R. Cirigolani, and M. De Vittorio. Stress-driven aln cantilever-based flow sensor for fish lateral line system. 88(8):2376–2378.

[22] Antonio Qualtieri, Francesco Rizzi, Gianmichele Epifani, Andres Ernits, Maarja Kruusmaa, and Massimo De Vittorio. Parylene-coated bioinspired artificial hair cell for liquid flow sensing. *Microelectronic Engineering*, 98(Complete):516–519.

[23] Ajay Giri Prakash Kottapalli, Mohsen Asadnia, Jianmin Miao, and Michael Triantafyllou. Touch at a distance sensing: lateral line inspired mems flow sensors. *Bioinspiration & Biomimetics*, 9(4):046011.

[24] Yonggang Jiang, Zhiqiang Ma, Jianchao Fu, and Deyuan Zhang. Development of a flexible artificial lateral line canal system for hydrodynamic pressure detection. *Sensors*, 17(6):1220, 2017.

[25] Ajay Giri Prakash Kottapalli, Meghali Bora, Mohsen Asadnia, Jianmin Miao, Subbu V Venkatraman, and Michael Triantafyllou. Nanofibril scaffold assisted mems artificial hydrogel neuromasts for enhanced sensitivity flow sensing. *Scientific reports*, 6(1):1–12, 2016.
Fish lateral line inspired perception and flow-aided control: A review

[26] Vicente Ignacio Fernandez, Stephen M Hou, Franz S Hover, Jeffrey H Lang, and Michael S Triantafyllou. Lateral-line inspired mems-array pressure sensing for passive underwater navigation. Technical report, Massachusetts Institute of Technology, Sea Grant College Program, 2007.

[27] Frank M Yaul, Vladimir Bulovic, and Jeffrey H Lang. A flexible underwater pressure sensor array using a conductive elastomer strain gauge. *Journal of microelectromechanical systems*, 21(4):897–907, 2012.

[28] Ajay GP Kottapalli, M Asadnia, JM Miao, George Barbastathis, and Michael S Triantafyllou. A flexible liquid crystal polymer mems pressure sensor array for fish-like underwater sensing. *Smart Materials and Structures*, 21(11):115030, 2012.

[29] Jack Chen, Zhifang Fan, Jun Zou, Jonathan Engel, and Liu Chang. Two-dimensional micromachined flow sensor array for fluid mechanics studies. *Journal of Aerospace Engineering*, 16(2):85–97, 2003.

[30] Yingchen Yang, Nannan Chen, Craig Tucker, Jonathan Engel, Saunvit Pandya, and Chang Liu. From artificial hair cell sensor to artificial lateral line system: development and application. In *2007 IEEE 20th International Conference on Micro Electro Mechanical Systems (MEMS)*, pages 577–580. IEEE, 2007.

[31] Nannan Chen, Jack Chen, Jonathan Engel, Saunvit Pandya, Craig Tucker, and Chang Liu. Development and characterization of high sensitivity bioinspired artificial haircell sensor. In *Proceedings of Solid-State Sensors, Actuators, and Microsystems Workshop*, volume 6, pages 4–8. Citeseer, 2006.

[32] Yingchen Yang, Nam Nguyen, Nannan Chen, Michael Lockwood, and Douglas L Jones. Artificial lateral line with biomimetic neuromasts to emulate fish sensing. *Bioinspiration & Biomimetics*, 5(1):16001, 2010.

[33] Mohsen Asadnia, Ajay Giri Prakash Kottapalli, Zhiyuan Shen, Jianmin Miao, and Michael Triantafyllou. Flexible and surface-mountable piezoelectric sensor arrays for underwater sensing in marine vehicles. *IEEE Sensors Journal*, 13(10):3918–3925, 2013.

[34] Mohsen Asadnia, Ajay Giri Prakash Kottapalli, K Domenica Karavitaki, Majid Ebrahimi Warkiani, Jianmin Miao, David P Corey, and Michael Triantafyllou. From biological cilia to artificial flow sensors: Biomimetic soft polymer nanosensors with high sensing performance. *Scientific reports*, 6:32955, 2016.

[35] Ahmad T Abdulssadda and Xiaobo Tan. Underwater source localization using an ipmc-based artificial lateral line. In *2011 IEEE International Conference on Robotics and Automation*, pages 2719–2724. IEEE, 2011.

[36] Mohsen Asadnia, Ajay Giri Prakash Kottapalli, Jianmin Miao, Majid Ebrahimi Warkiani, and Michael S Triantafyllou. Artificial fish skin of self-powered micro-electromechanical systems hair cells for sensing hydrodynamic flow phenomena. *Journal of the Royal Society Interface*, 12(111):20150322, 2015.

[37] Gijs Krijnen, Theo Lammerink, Remco Wiegerink, and Jérôme Casas. Cricket inspired flow-sensor arrays. In *SENSORS, 2007 IEEE*, pages 539–546. IEEE, 2007.

[38] JB Stocking, WC Eberhardt, YA Shakhshir, BH Calhoun, JR Paulus, and M Appleby. A capacitance-based whisker-like artificial sensor for fluid motion sensing. In *SENSORS, 2010 IEEE*, pages 2224–2229. IEEE, 2010.

[39] JJ Van Baar, Marcel Dijkstra, RJ Wiegerink, TSJ Lammerink, and GJM Krijnen. Fabrication of arrays of artificial hairs for complex flow pattern recognition. In *SENSORS, 2003 IEEE*, volume 1, pages 332–336. IEEE, 2003.

[40] N Izadi, Meint J de Boer, Johan W Berenschot, and Gijsbertus JM Krijnen. Fabrication of superficial neuromast inspired capacitive flow sensors. *Journal of micromechanics and microengineering*, 20(8):085041, 2010.

[41] Adrian Klein and Horst Bleckmann. Determination of object position, vortex shedding frequency and flow velocity using artificial lateral line canals. *Beilstein journal of nanotechnology*, 2(1):276–283, 2011.

[42] Sebastian Große and Wolfgang Schröder. The micro-pillar shear-stress sensor mps3 for turbulent flow. *Sensors*, 9(4):2222–2251, 2009.

[43] Ben J Wolf, Jonathan AS Morton, William N MacPherson, and Sietse M Van Netten. Bio-inspired all-
Fish lateral line inspired perception and flow-aided control: A review

[44] Saunvit Pandya, Yingchen Yang, Douglas L Jones, Jonathan Engel, and Chang Liu. Multisensor processing algorithms for underwater dipole localization and tracking using mems artificial lateral-line sensors. *EURASIP Journal on Advances in Signal Processing*, 2006(1):076593, 2006.

[45] Peng Liu, Rong Zhu, and Ruiyi Que. A flexible flow sensor system and its characteristics for fluid mechanics measurements. *Sensors*, 9(12):9533–9543, 2009.

[46] Yingchen Yang, Jack Chen, Jonathan Engel, Saunvit Pandya, Nannan Chen, Craig Tucker, Sheryl Coombs, Douglas L Jones, and Chang Liu. Distant touch hydrodynamic imaging with an artificial lateral line. *Proceedings of the National Academy of Sciences*, 103(50):18891–18895, 2006.

[47] Jack Chen, Jonathan Engel, Nannan Chen, Saunvit Pandya, Sheryl Coombs, and Chang Liu. Artificial lateral line and hydrodynamic object tracking. In *19th IEEE International Conference on Micro Electro Mechanical Systems*, pages 694–697. IEEE, 2006.

[48] Siddhartha Verma, Costas Papadimitriou, Nora Lüthen, Georgios Arampatzis, and Petros Koumoutsakos. Optimal sensor placement for artificial swimmers. *Journal of Fluid Mechanics*, 884, 2020.

[49] Dong Xu, Zhiyu Lv, Haining Zeng, Hadjar Bessaïh, and Bing Sun. Sensor placement optimization in the artificial lateral line using optimal weight analysis combining feature distance and variance evaluation. *ISA transactions*, 86:110–121, 2019.

[50] Roberto Venturelli, Otar Akanyeti, Francesco Visentin, Jaas Ježov, Lily D Chambers, Gert Toming, Jennifer Brown, Maarja Kruusmaa, William M Megill, and Paolo Fiorini. Hydrodynamic pressure sensing with an artificial lateral line in steady and unsteady flows. *Bioinspiration & biomimetics*, 7(3):036004, 2012.

[51] Taavi Salumäe and Maarja Kruusmaa. Flow-relative control of an underwater robot. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 469(2153):20120671, 2013.

[52] Juan Francisco Fuentes-Pérez, Jeffrey A Tuhtan, Ruth Carbonell-Baeza, Mark Musall, Gert Toming, Naveed Muhammad, and Maarja Kruusmaa. Current velocity estimation using a lateral line probe. *Ecological engineering*, 85:296–300, 2015.

[53] Jeffrey A Tuhtan, Juan Francisco Fuentes-Perez, Gert Toming, Matthias Schneider, Richard Schwarzenberger, Martin Schletterer, and Maarja Kruusmaa. Man-made flows from a fish’s perspective: autonomous classification of turbulent fishway flows with field data collected using an artificial lateral line. *Bioinspiration & biomimetics*, 13(4):046006, 2018.

[54] Guijie Liu, Shuikuan Liu, Shirui Wang, Huanhuan Hao, and Mengmeng Wang. Research on artificial lateral line perception of flow field based on pressure difference matrix. *Journal of Bionic Engineering*, 16(6):1007–1018, 2019.

[55] Nataliya Strokina, Joni-Kristian Kämäräinen, Jeffrey A Tuhtan, Juan Francisco Fuentes-Pérez, and Maarja Kruusmaa. Joint estimation of bulk flow velocity and angle using a lateral line probe. *IEEE Transactions on Instrumentation and Measurement*, 65(3):601–613, 2015.

[56] Jeffrey A Tuhtan, Juan Francisco Fuentes-Perez, Gert Toming, and Maarja Kruusmaa. Flow velocity estimation using a fish-shaped lateral line probe with product-moment correlation features and a neural network. *Flow Measurement and Instrumentation*, 54:1–8, 2017.

[57] Guijie Liu, Huanhuan Hao, Tingting Yang, Shuikuan Liu, Mengmeng Wang, Atilla Incecik, and Zhixiong Li. Flow field perception of a moving carrier based on an artificial lateral line system. *Sensors*, 20(5):1512, 2020.

[58] Zheng Ren and Kamran Mohseni. A model of the lateral line of fish for vortex sensing. *Bioinspiration & biomimetics*, 7(3):036016, 2012.

[59] Brian Free, Mukund K Patnaik, and Derek A Paley. Observability-based path-planning and flow-relative control of a bioinspired sensor array in a karman vortex street. In *2017 American Control Conference (ACC)*, pages 548–554. IEEE, 2017.

[60] Brian A Free and Derek A Paley. Model-based observer and feedback control design for a rigid joukowski foil in a kármán vortex street. *Bioinspiration & biomimetics*, 13(3):035001, 2018.

[61] Horst Bleckmann. Reception of hydrodynamic stimuli in aquatic and semiaquatic animals. 1994.

[62] Zhijie Tang, Zhen Wang, Jiaqi Lu, Gaoqian Ma, and Pengfei Zhang. Underwater robot detection system
based on fish's lateral line. *Electronics*, 8(5):566, 2019.

[63] Xiande Zheng, Yong Zhang, Mingjiang Ji, Ying Liu, Xin Lin, Jing Qiu, and Guanjun Liu. Underwater positioning based on an artificial lateral line and a generalized regression neural network. *Journal of Bionic Engineering*, 15(5):883–893, 2018.

[64] Xin Lin, Yong Zhang, Mingjiang Ji, Xiande Zheng, LV Kehong, Jing Qiu, and Guanjun Liu. Dipole source localization based on least square method and 3d printing. In *2018 IEEE International Conference on Mechatronics and Automation (ICMA)*, pages 2203–2208. IEEE, 2018.

[65] Ahmad T Abdulnsadda and Xiaobo Tan. Nonlinear estimation-based dipole source localization for artificial lateral line systems. *Bioinspiration & biomimetics*, 8(2):026005, 2013.

[66] Ali Ahrari, Hong Lei, Montassar Aidi Sharif, Kalyanmoy Deb, and Xiaobo Tan. Design optimization of an artificial lateral line system incorporating flow and sensor uncertainties. *Engineering Optimization*, 49(2):328–344, 2017.

[67] Wei-Kuo Yen and Jenhwa Guo. Phase controller for a robotic fish to follow an oscillating source. *Ocean Engineering*, 161:77–87, 2018.

[68] Guijie Liu, Shuxian Gao, Th Sarkodie-Gyan, and Zhixiong Li. A novel biomimetic sensor system for vibration source perception of autonomous underwater vehicles based on artificial lateral lines. *Measurement Science and Technology*, 29(12):125102, 2018.

[69] Xuefei Chen, Guoming Zhu, Xiaojian Yang, David LS Hung, and Xiaobo Tan. Model-based estimation of flow characteristics using an ionic polymer–metal composite beam. *IEEE/ASME Transactions on Mechatronics*, 18(3):932–943, 2012.

[70] Ahmad T Abdulnsadda and Xiaobo Tan. Localization of a moving dipole source underwater using an artificial lateral line. In *Bioinspiration, Biomimetics, and Bioreplication 2012*, volume 8339, page 833909. International Society for Optics and Photonics, 2012.

[71] AMK Dagamseh, Theodorus SJ Lammerink, CM Bruinink, Remco J Wiegerink, and Gijsbertus JM Krijnen. Dipole source localisation using bio-mimetic flow-sensor arrays. *Procedia chemistry*, 18(3):932–943, 2012.

[72] AMK Dagamseh, Theodorus SJ Lammerink, ML Kolster, CM Bruinink, Remco J Wiegerink, and Gijsbertus JM Krijnen. A simulation study of the dipole source localisation applied on bio-mimetic flow-sensor linear array. In *12th Annual Workshop on Semiconductor Advances for Future Electronics and Sensors (SAFE)*, pages 534–537. Technology Foundation (STW), 2009.

[73] AMK Dagamseh and Gijsbertus JM Krijnen. Map estimation of air-flow dipole source positions using array signal processing. In *Annual Workshop on Semiconductor Advances for Future Electronics and Sensors, SAFE 2010*. Technology Foundation (STW), 2010.

[74] AMK Dagamseh, Theodorus SJ Lammerink, ML Kolster, CM Bruinink, Remco J Wiegerink, and Gijsbertus JM Krijnen. Dipole-source localization using biomimetic flow-sensor arrays positioned as lateral-line system. *Sensors and actuators A: Physical*, 162(2):355–360, 2010.

[75] Ahmad Dagamseh, Remco Wiegerink, Theo Lammerink, and Gijs Krijnen. Imaging dipole flow sources using an artificial lateral-line system made of biomimetic hair flow sensors. *Journal of the Royal Society Interface*, 10(83):20130162, 2013.

[76] Mingjiang Ji, Yong Zhang, Xiande Zheng, Xin Lin, Guanjun Liu, and Jing Qiu. Resolution improvement of dipole source localization for artificial lateral lines based on multiple signal classification. *Bioinspiration & biomimetics*, 14(1):016016, 2018.

[77] Mingjiang Ji, Yong Zhang, Xiande Zheng, Xin Lin, Guanjun Liu, and Jing Qiu. Performance evaluation and analysis for dipole source localization with lateral line sensor arrays. *Measurement Science and Technology*, 30(11):115107, 2019.

[78] Ben J Wolf and Sietse M van Netten. Hydrodynamic imaging using an all-optical 2d artificial lateral line. In *2019 IEEE Sensors Applications Symposium (SAS)*, pages 1–6. IEEE, 2019.

[79] Ben J Wolf, Steven Warmelink, and Sietse M van Netten. Recurrent neural networks for hydrodynamic imaging using a 2d-sensitive artificial lateral line. *Bioinspiration & biomimetics*, 14(5):055001, 2019.

[80] BENJ WOLF, PRIMOZ PIRIH, MAARJA KRUUSMAA, and SIETSE M VAN NETTEN. Shape classification using hydrodynamic detection via a sparse large-scale 2d-sensitive artificial lateral line.
Fish lateral line inspired perception and flow-aided control: A review

2020.

[81] Xingwen Zheng, Minglei Xiong, and Guangming Xie. Data-driven modeling for superficial hydrodynamic pressure variations of two swimming robotic fish with leader-follower formation. In 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC), pages 4331–4336. IEEE, 2019.

[82] Chengcai Wang, Wei Wang, and Guangming Xie. Speed estimation for robotic fish using onboard artificial lateral line and inertial measurement unit. In 2015 IEEE International Conference on Robotics and Biomimetics (ROBIO), pages 285–290. IEEE, 2015.

[83] Feitian Zhang, Francis D Lagor, Derrick Yeo, Patrick Washington, and Derek A Paley. Distributed flow sensing for closed-loop speed control of a flexible fish robot. Bioinspiration & biomimetics, 10(6):065001, 2015.

[84] Levi DeVries, Francis D Lagor, Hong Lei, Xiaobo Tan, and Derek A Paley. Distributed flow estimation and closed-loop control of an underwater vehicle with a multi-modal artificial lateral line. Bioinspiration & biomimetics, 10(2):025002, 2015.

[85] Nora Martiny, Stefan Sosnowski, Kolja Kühnlenz, Sandra Hirche, Yimin Nie, Jan-Moritz P Franosch, and J Leo Van Hemmen. Design of a lateral-line sensor for an autonomous underwater vehicle. IFAC Proceedings Volumes, 42(18):292–297, 2009.

[86] Wei-Kuo Yen, Daniel Martinez Sierra, and Jenhwa Guo. Controlling a robotic fish to swim along a wall using hydrodynamic pressure feedback. IEEE Journal of Oceanic Engineering, 43(2):369–380, 2018.

[87] Otar Akanyeti, Lily D Chambers, Jaas Ježov, Jennifer Brown, Roberto Venturelli, Maarja Kruusmaa, William M Megill, and Paolo Fiorini. Self-motion effects on hydrodynamic pressure sensing: part i. forward–backward motion. Bioinspiration & biomimetics, 8(2):026001, 2013.

[88] Xingwen Zheng, Wei Wang, Minglei Xiong, and Guangming Xie. Online state estimation of a fin-actuated underwater robot using artificial lateral line. IEEE Transactions on Robotics, 36(2):472–487, 2020.

[89] Hongli Liu, Kun Zhong, Yating Fu, Guangming Xie, and Qixin Zhu. Pattern recognition for robotic fish swimming gaits based on artificial lateral line system and subtractive clustering algorithms. Sensors & Transducers, 182(11):207, 2014.

[90] Maarja Kruusmaa, Paolo Fiorini, William Megill, Massimo de Vittorio, Otar Akanyeti, Francesco Visentin, Lily Chambers, Hadi El Daou, Maria-Camilla Fiazza, Jaas Ježov, et al. Filose for svenning: A flow sensing bioinspired robot. IEEE Robotics & Automation Magazine, 21(3):51–62, 2014.

[91] Taavi Salumäe, Inaki Ranó, Otar Akanyeti, and Maarja Kruusmaa. Against the flow: A braitenberg controller for a fish robot. In 2012 IEEE International Conference on Robotics and Automation, pages 4210–4215. IEEE, 2012.

[92] Wei Wang, Yuan Li, Xingxing Zhang, Chen Wang, Shiming Chen, and Guangming Xie. Speed evaluation of a freely swimming robotic fish with an artificial lateral line. In 2016 IEEE International Conference on Robotics and Automation (ICRA), pages 4737–4742. IEEE, 2016.

[93] Francis D Lagor, Levi D DeVries, Kathryn M Waychoff, and Derek A Paley. Bio-inspired flow sensing and control: Autonomous underwater navigation using distributed pressure measurements. In Proc. 18th Int. Symp. Unmanned Untethered Submersible Technol., pages 1–8, 2013.

[94] Wei Wang, Xingxing Zhang, Jianwei Zhao, and Guangming Xie. Sensing the neighboring robot by the artificial lateral line of a bio-inspired robotic fish. In 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pages 1565–1570. IEEE, 2015.

[95] Xingwen Zheng, Chen Wang, Ruifeng Fan, and Guangming Xie. Artificial lateral line based local sensing between two adjacent robotic fish. Bioinspiration & biomimetics, 13(1):016002, 2017.
[98] Xingwen Zheng, Manyi Wang, Junzheng Zheng, Runyu Tian, Minglei Xiong, and Guangming Xie. Artificial lateral line based longitudinal separation sensing for two swimming robotic fish with leader-follower formation. In *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 2539–2544. IEEE, 2019.

[99] Naveed Muhammad, Nataliya Strokina, Gert Toming, Jeffrey Tuhtan, Joni-Kristian Kämäräinen, and Maarja Kruusmaa. Flow feature extraction for underwater robot localization: Preliminary results. In *2015 IEEE International Conference on Robotics and Automation (ICRA)*, pages 1125–1130. IEEE, 2015.

[100] Juan Francisco Fuentes-Pérez, Naveed Muhammad, Jeffrey A Tuhtan, Ruth Carbonell-Baeza, Mark Musall, Gert Toming, and Maarja Kruusmaa. Map-based localization in structured underwater environment using simulated hydrodynamic maps and an artificial lateral line. In *2017 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, pages 128–134. IEEE, 2017.