A simple macro-scale artificial lateral line sensor for the detection of shed vortices

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Abstract

Underwater robot sensing is challenging due to the complex and noisy nature of the environment. The lateral line system in fish allows them to robustly sense their surroundings, even in turbid and turbulent environments, allowing them to perform tasks such as shoaling or foraging. Taking inspiration from the lateral line system in fish to design robot sensors could help to power underwater robots in inspection, exploration, or environmental monitoring tasks. Previous studies have designed systems that mimic both the design and the configuration of the lateral line and neuromasts, but at high cost or using complex procedures. Here, we present a simple, low cost, bio-inspired sensor, that can detect passing vortices shed from surrounding obstacles or upstream fish or robots. We demonstrate the importance of the design elements used, and show a minimum 20% reduction in residual error over sensors lacking these elements. Results were validated in reality using a prototype of the artificial lateral line sensor. These results mark an important step in providing alternate methods of control in underwater vehicles that are simultaneously inexpensive and simple to manufacture.

1. Introduction

Complex fluid dynamics in underwater environments make it difficult to design sensors that are effective at detecting and interpreting the surroundings of underwater robots. As a result, many of the underwater robotic platforms in use at the moment require the use of tethers and an operator to complete the sensory tasks required of them [1, 2]. Other platforms are able to use visual processing techniques to effectively navigate autonomously, however in areas with low light or high turbidity this is more difficult [3]. Additionally, there are a number of challenges that exist when attempting to form swarms of underwater robots as they must also be able to sense and communicate with each other [4–7]. However, the benefits that swarms can bring are numerous, including increases in fault tolerance, highly beneficial in the extreme ocean environment, and parallel processing capacity, useful given the ocean’s vast area [8]. Applications could then include underwater inspection, search and rescue, exploration, or environmental monitoring [9, 10].

To help deal with these problems, we turn to nature for inspiration. Many of the creatures found in the sea have adapted their senses for better use underwater and even developed entirely new ones. An adaptation of the auditory systems in many cetaceans allows them the use of sonar to aid in navigation [11], while fish like the Peters’ elephantnose fish [12] and the black ghost knifefish [13] are able to actively generate an electric field for the same purpose. Another sense that teleost fishes possesses is the lateral line [14–17]. The lateral line is comprised of two types of sensory units, superficial neuromasts and canal neuromasts [15, 16, 18], that detect the surrounding flow velocities and accelerations [18, 19]. Neuromasts are small hair-like structures that either exist on the skin (superficial neuromast) or in a system of canals that sit beneath the skin (canal neuromast); these sub-dermal canals have small openings, pores, that allow the canal neuromasts to gather information from their surroundings [14–17]. The lateral line is comprised of two types of sensory units, superficial neuromasts and canal neuromasts [15, 16, 18], that detect the surrounding flow velocities and accelerations [18, 19]. Neuromasts are small hair-like structures that either exist on the skin (superficial neuromast) or in a system of canals that sit beneath the skin (canal neuromast); these sub-dermal canals have small openings, pores, that allow the canal neuromasts to gather information from their surroundings [14, 20]. It has been shown that some fish are able to navigate, hunt and shoal by relying solely on the lateral line [20–27]. The lack of light available to cave dwelling fish and the issues of scattering and absorption that autonomous underwater vehicles (AUVs) at depth or in highly turbid water experience [28, 29] share some overlap, and the cave dwellers rely heavily on their lateral
Bioinspir. Biomim. lines to overcome this [25, 26]. As such, a new type of sensory suite inspired by the lateral line seems a prudent way to overcome these issues in AUVs too.

A number of biologically inspired artificial lateral line sensors do exist and have been shown to be effective [30–38], but they often use micro-mechanical-electro systems (MEMS) which can be difficult to manufacture [39–41]. While many MEMS processes are batch processes, and as such they are able to produce large numbers of sensors for relatively low cost, the complexity of the manufacturing processes involved can require specialist equipment. Given that the ultimate aim of this project is to bring the artificial lateral line to underwater robotic swarms, a complex design or manufacturing process, with its complex manufacturing equipment, will increase both the time and the cost required to reach the final product. The large scale of the ocean environment dictates that many agents are required for any swarm operating there to be effective and as such all efforts must be made to reduce these, otherwise the swarm will require too many resources to ever be feasible. A number of other systems exist that are able to combine off-the-shelf sensing units, particularly pressure sensors, into an effective artificial lateral line that is less complex than the systems above [42–45]. However, even these systems require the use and subsequent coordination of multiple pressure sensors for effective flow sensing, which can again drive up cost. Further work is needed to create a novel design of very simple sensor that can operate effectively without requiring multiple instances of itself.

Here, we propose a new design for a simple and low-cost artificial lateral line system composed of a neuromast and bio-inspired canal structure. Our design differs from other more conventional canal neuromast designs due to its u-bend shaped front and rear facing pores; this helps filter background flow more effectively. These design changes are introduced as a result of study by the authors looking at how variations in the shape of the lateral line affect functionality [46]. Additionally, it is macro scale in size which makes it significantly easier to manufacture. In fluid dynamics, varying scales can drastically alter flow properties, and as a result much of the work that has come before this has stayed true to the expected biological scales. However, this project wanted to test if macroscopic artificial lateral lines could also function effectively. A potential risk of this design choice was that the larger sensor body could alter the flow field, but as we demonstrate here, the differences, if any, are not enough to prevent the sensor from functioning properly. We also deem the benefits of being able to manufacture this sensor using mostly 3D printing and without the need for special equipment to outweigh the downsides. The design also differs from previous work by using a highly flexible membrane as a fulcrum about which a stiff element will rotate, transferring force from the fluid within the sensor to the other side of the membrane. The sensor is designed to detect shed vortices, which are often formed by the swimming motions of upstream fish (natural or robotic), or obstacles. Being able to detect the vortices shed behind obstacles would give an AUV improved environmental awareness, while detecting swimming neighbours can aid in navigation and coordination. We highlight the ability of this novel canal lateral line sensor to filter background flow and its sensitivity to the shed vortices left in the wake of swimming neighbours, building on some preliminary work. We demonstrate in simulation that the sensor can detect shedding vortex patterns emanating from a cylinder used to mimic an upstream fish or an obstacle [47–49]. We then justify the design specifications by comparing our sensor to variations reflecting each design decision. Results show the importance of all design decisions in improving similarity between the signal detected by the sensor and the original signal. The end result showed a 20% improvement over the previous one [50]. Based on these results, we produced a physical sensor using off-the-shelf low cost parts and 3D printing and demonstrated its ability to sense shed vortices in water.

2. Methods

2.1. Optimising the lateral line

Our previous work has detailed an initial investigation into the use of a canal structure to filter background flow and into the effects of varying pore size on sensitivity [50]. The lateral line structure in fish resembles a long tube with a number of openings along a roughly 1D line on one side. The pores allow information from the external fluid flow to be transferred to the fluid within the canal where it can be interpreted by the fish. The sensor designed in the previous work is meant to represent a closed section of this canal, and used a cuboid with two circular holes on the same face (to represent pores), and a hair cell within the sensor on the internal face opposite these holes. Flow velocities were measured within the sensor and also within the flow field in the absence of a sensor. Effectiveness was measured by finding the detected (the flow velocities within the sensor) and expected (flow velocities in open flow) time series’ residuals through Euclidean distance measures. Data from this showed that the canal structure was effective at filtering background flow and that increasing pore size increases internal flow speed, in turn resulting in increased sensitivity. However, signal integrity was not well maintained.

From the work by Scott et al, we hypothesised that three key design changes were needed to reduce residual error, namely the use of circular channels, the use of rear-facing pores, and the use of increased spacing between pores [50]. These changes stemmed from observations made in simulations with two
major issues being noted: that passing vortices were not affecting pores in the expected way, and that turbulence was being established within the sensor and sometimes persisting after the vortex was gone. The change from a square canal design to a circular canal design was to help reduce the internal turbulence and was inspired by both biology, the canals seen in the lateral line not being square in shape [51], and aerodynamics, where flow around corners in square ducts are associated with high turbulence and vorticity [52, 53].

The expected mechanism of the original sensor was that the passing vortex would move flow in the downstream pore and then back out of the upstream pore, but this was not always the case, as vortices often affected only the upstream pore or both pores at the same time. The use of a rear facing pore was also inspired by biology, with the channels that lead from pore to sub-dermal canal tending to face backwards and with scales as well often occluding the pore’s upstream side [51], and while there is limited data on how the angle of the canal affects how flow and turbulence is interpreted, we hypothesise it will help to reduce interference from background flow. The increased distance between pores was introduced to help prevent passing vortices affecting both pores at the same time and ensure that any vortex was being detected only by the desired pore.

To verify that the design changes improved the sensor, additional designs, with one of these elements missing or altered, were created and compared to the optimised sensor. AutoDesk fusion was used to create all designs.

### 2.2. Artificial lateral line design

Inspired by its natural counterpart, our optimised artificial lateral line sensor has a canal, two pores, and one neuromast embedded in the canal. The sensor is formed of a long curved tube with the bottom shorter part dedicated to detecting the vortex and hosting the artificial neuromast hair, while the longer part acts as the canal and neutral pressure reservoir (figure 1(a)). This neutral pressure space then allows a pressure differential to be created when the negative pressure at the centre of a vortex passes the mouth, resulting in fluid accelerating out of the canal and deflecting the artificial neuromast (figure 1(c)).

The design hinges around the idea of using a stiff rod to act as the neuromast, with half of this rod inside the canal and half outside, and a thin elastic membrane, positioned at the midpoint of the rod, to act as a fulcrum (figure 1(b)). In this way, fluid motion within the sensor causes the external end of the rod to exhibit an equal and opposite motion. The highly elastic membrane offers almost no resistance, allowing the neuromast to swing freely, and removing the need to simulate a neuromast; fluid velocity is taken as a proxy for neuromast deflection as with minimal resistance the two will be very closely related. Dimensions were chosen to be easy to produce using 3D printing and off-the-shelf components: 140 mm long, 39 mm wide and 32 mm in height (figure 1(b)).

The sensor is meant to align with the fluid direction, with pores opening in the opposite direction. This prevents interference on the neuromast due to water displacement (e.g. river flow) or robot motion from impacting the sensory readout (figure 1(c)).

It is worth noting the difference in scale between this design and that of the biological lateral line: with changing scales, the associated Reynolds number will also change and with it, the flow properties of the system as a whole. The Reynolds number are calculated using:

$$Re = \frac{\rho V D}{\mu}$$

Within the sensor, $\rho = 1$ for the density of water, $\mu = 1$ for the dynamic viscosity of water at 18 degrees, $V = 0.0025 \text{ m s}^{-1}$ as the maximum speed of water flow within the sensor, taken from data extracted from simulations, and $D$ as 15 mm from channel diameter. As flow velocity within the sensor varies with time, this gives:

$$0 < Re < 375.$$  

Externally:

$$10 000 < Re < 70 000.$$  

With water density and dynamic viscosity being maintained, but using $V = 0.5 \text{ m s}^{-1}$ and with $D$ being either 20 mm or 140 mm, referring to the lengths of the short and long canals respectively.

### 2.3. Simulation-based experiments

To predict the expected sensory readout from the artificial lateral line and optimise its design, we simulate an environment with flow (due to robot motion or water motion), and a cylinder to generate vortices in lieu of an upstream fish, robot or obstacle. Simulations were created with OpenFOAM at 0.5 m s$^{-1}$. The simulated area was either 400 or 500 mm (depending on the length of the sensor in the simulation) by 200 mm by 250 mm, using 800 103 cells. A cylinder of 100 mm diameter was included as a vortex generator. Our sensor was placed 200 mm behind the cylinder and 40 mm to the side of the cylinder’s centre line, as analysis of flow behind the cylinder indicated that this point has the maximum flow velocity variation, and hence is the point from which the most information can be extracted [50]. Simulations used the semi-implicit method for pressure linked equations algorithm coupled with a Reynolds-averaged Navier-Stokes equations to get a steady-state approximation of the Kármán vortex street. The SST k-omega model is used for turbulence calculations. Data was extracted along a line in the vertical plane that extended between the two internal walls of the sensor. The data was extracted in the form of $x$ velocities along the length of the line,
which was then averaged. No neuromast is simulated as in the experiment the combination of a stiff hair coupled with a highly flexible membrane as a base makes the neuromast extremely sensitive to velocities, and as such the measured velocity can be considered a proxy for neuromast deflection. Experiments are performed using the computational fluid dynamics simulator OpenFOAM. Data was visualised using ParaFOAM, the post-processing element of the OpenFOAM software, but additional analysis was done in MATLAB: velocity data from each point in the mesh was exported to an excel file, which was then imported into MATLAB.

### 2.4. Signal analysis

Signal processing analysis was done to determine which of the sensor designs was most effective at both detecting vortices and retaining signal integrity. For each design, Euclidean distance measures are used to compare the residual error between the time series of detected velocities inside the sensor and the time series of expected velocities in the absence of the sensor:

\[ d = \sqrt{\sum (v_p - v_q)^2}, \]

where \( v_p \) and \( v_q \) are the timeseries \( p \) and \( q \), and \( d \) is the total residual between them.

Time series are normalised (with \( \mu = 0 \) and \( \text{std} = 1 \)) before residuals are calculated to make comparison between residuals easier:

\[ \hat{v}_p = (v_p - \bar{v}_p)/\sigma, \]

where \( v_p \) is the time series, \( \hat{v}_p \) is the normalised time series, \( \bar{v}_p \) is the mean of the time series and \( \sigma \) is the standard deviation of the time series.

The design with the lowest residual is then said to be the most optimised. Identical signals will have a residual of zero. For reference, comparison with the inverse of the expected time series \((v_p^*(-1))\) gives a residual of 0.0282. Stl files were exported from AutoDesk and into OpenFOAM using the snappy-hexmesh capability. A water flow of 0.5 m s\(^{-1}\) was used as a realistic speed for an AUV [54], and the

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**Figure 1.** Diagram of the simulated and physical sensors and their operation. (A) A simulated sensor, showing its dimensions and the position of the ‘artificial neuromast’. The artificial neuromast in this case is a line of points within the mesh (marked) at which flow velocity information is recorded. The average velocity across these points is used for the final data sets. (B) The 3D printed sensor and the physical adaptations from the simulated sensor required for its operation. Instead of taking velocity data along the artificial neuromast mesh line, the ‘visual tracker’ was used instead. An LED covered in black tape was inserted through a highly flexible membrane that allowed free motion of the visual tracker. Tape was wrapped around the pins within the sensor to increase surface area and cause greater deflections in response to fluid motion. Visual tracker motion is opposite to that of the fluid motion. (C) The sensor operating within the simulated environment. The negative pressure at the centre of the passing vortex results in a pressure differential with the neutral pressure within the long canal part of the sensor. This results in water motion that can be detected by observing the deflection of the visual tracker. Figure not to scale.
simulation was allowed to run for 400 s to allow it to reach a steady state solution.

2.5. Artificial lateral line production and experiments

Our optimised sensor (figure 1(c)) was 3D printed using a Form 2 printer and Clear V4 resin. A 7 × 7 mm window was cut into the short side of the sensor to add the artificial neuromast. Our neuromast consists of an unpowered LED with a layer of cloth adhesive-tape attached between the pins to increase the surface area affected by the flows; an LED was used for convenience, but a 3D printed structure with a high contrast head for tracking and a plate to receive fluid force could have been used. The LED bulb was coloured with black to increase contrast, and is henceforth referred to as the visual tracker. A 10 × 10 mm square of elastic material was used to cover the window, and the pins of the LED were pushed through this, so that the visual tracker remains outside the sensor; the fabric was added after this stage. The taped pins of the LED are exposed to the flow within the sensor and deflect in response to changing velocities. The 10 × 10 mm square represents the highly elastic membrane discussed earlier and acts as a fulcrum, allowing the neuromast hair to swing freely. The movement of the visual tracker indicates deflections of the pins inside the sensor as a response to shed vortices. A camera is used to record the motion of the visual tracker to produce the sensory output. Several of the design decisions discussed here were due to the Covid-19 pandemic limiting access to certain resources.

Preliminary experiments were undertaken to demonstrate the physical sensor’s ability to filter the laminar background flow and to detect shed vortices. To demonstrate the former, the sensor was moved through a static container of water at a steady speed, in approximation of having a steady laminar flow being passed around the sensor. This was done to demonstrate that the laminar flow, typically background flow, would be filtered out and not result in immediate saturation of our neuromast; saturation occurs when the visual tracker reaches its position of maximum deflection. This is undesirable as after this point no additional information can be extracted from the surroundings, such as from turbulent flows. To demonstrate the latter, the sensor was held stationary in a large container of water and a cylinder measuring 100 mm in diameter was pulled through the water alongside the sensor. Speeds and distances were varied to test the conditions over which the sensor was able to function without information saturation and to detect a vortex. Each pass was recorded. Any motion of the visual tracker was tracked as a way of indicating that the sensor had been successful.

Further experiments were also conducted in a custom-built flow tank, consisting of a test area and a water reservoir (figure 2). The reservoir was filled using an external water source, before being allowed to flow through the test area. A 100 mm diameter plastic cylinder was placed into the centre of the test area to generate the necessary vortices. Windows were cut into the top surface of the test area to allow the sensor to be positioned in different locations behind the cylinder (figure 2). A camera was positioned 150 mm away from the top of the arena and set to record in 1080p at 30 fps. Footage was analysed frame by frame in the image processing software GIMP, where each video was given a global coordinate system centred on the bottom of the sensor opening, and movement of a fixed point on the visual tracker was recorded against this system; the fixed point varied between videos so all graphs were adjusted to be centred around 0.

3. Results

Simulations were run to verify if the design changes discussed above, namely changing from square channels to fixed diameter channels, using pores that face backwards instead of sideways, and increasing the distance between the pores. Across all of these results we saw a mean improvement (measured by percentage difference) of 23%, and a maximum improvement of 39% (fixed diameter channel vs square channel). We then demonstrate experimentally that the optimised design is able to filter background flow and detect shed vortices, both when stationary and in flow.

3.1. Fixed diameter internal channels prevent internal turbulence

We aimed to minimise internal turbulence by setting a fixed circular diameter for the internal channels. Our observation was that the internal shape of the sensor, i.e. using a square canal vs a circular canal, could cause this. This issue was particularly pronounced in structures with corners, as internal turbulence had a tendency to linger between vortices, adding significant noise to multiple cycles of the waveform. We theorised that removing the empty corners and instead having just a channel of fixed radius would reduce or even remove the internal turbulence levels.

Figure 3 shows the improvement seen when using a circular canal design (a), as opposed to a square canal design (b). While there are parts of the square canal’s time-series that appear to overlap well with that of our design’s, the majority of it is different to both ours and the original signal. Comparison between the residuals reveal that the square canal has a residual error of 0.0231, almost 40% more error than what is detected by the square channel compared to our final optimised design.

3.2. Rear facing pores reduce noise

The orientation of the sensor was chosen to reduce the amount of background flow (from sensor motion or laminar water flow) entering the sensor and disrupting the vortex measurement. To demonstrate
Figure 2. The physical experiment used to test the 3D printed sensor. A flow tank, consisting of a large water reservoir and an observation area, was designed and built to test the response of the 3D printed sensor to vortices shed by a cylinder in flow. Responses are measured through observation of the motion of the visual tracker (an LED bulb covered with black tape) that deflects in response to a passing vortex. The cylinder was placed in the observation area, and the 3D printed sensor was affixed in a number of locations (marked by the lettered circles) downstream. A chimney structure was used to allow the sensor to be placed fully into the flow without having the flow interfere with the tracker response, and also to affix the sensor in place; this was done by fixing the top of the chimney to the underside of a clear perspex sheet, which was then placed into the observation window and fixed in place. The long side of the sensor is shorter here than in the simulations, as it was found that this length did not matter, as long as a neutral pressure reservoir was maintained. Images are not to scale.

the effect of orientation, we compare the optimised sensor design against a sensor designed with a single side-facing pore and a single forward-facing pore (figure 4). Comparing errors reveals that the optimised design is approximately 20% better than either (b) or (c). The design in figure 4(c) also experiences significantly higher velocity on the neuromast which effectively removes the filtering property of the sensor. The side-facing pore (figure 4(b)) offers significant improvement over this but is, again, not as effective as the rear-facing pore.

3.3. Further spaced pores result in less interference

Increasing the spacing between pores was done to reduce the ability of a vortex to affect both pores at the same time, leading to interference. We observed that when pores were in close proximity to each other, vortices affected both simultaneously. In real terms, this meant that both pores were experiencing an in-flow (or out-flow) at the same time, particularly during the early (or late) stages of a passing vortex being detected, which resulted in either no velocity on the neuromast as the flows from the two pores cancelled each other out, or in a noisy signal. We theorised that having the two pores further apart would make it less likely that both pores could be affected by the same signal at the same time.

Figure 5 shows that the design with the pores in close proximity (b) displays approximately 20% greater error than our design. Increasing the spacing between pores in a direction perpendicular to flow appears to reduce accuracy, with the widely spaced pore design (c) having over 25% more error than our optimised design. Both of these designs do retain their filtering properties though.

Our design is inspired by the structure of the lateral line, particularly the subdermal canal part of the lateral line, with the u-bend and opening imitating as in gill pore. The initial work by Scott et al was more focussed on including two pores, which were then connected to a limited section of the subdermal canal [50]. Based on the results above, it appears that the longer section of canal has a greater effect on allowing the sensor to extract information properly from the surroundings. This represents a shift from trying to capture bulk water movement to capturing changing pressures: the previous sensor attempted to sense water moving into the downstream pore of the sensor, deflecting the neuromast, and then exiting from the upstream pore. This mechanism was very susceptible
to noise due to the sensor sometimes having flow enter the upstream pore instead of the downstream pore or enter both pores together. Both pores were also being affected by the negative pressure of the passing vortex too. Neglecting water motion allowed us to eliminate much of the noise in the original signal. The increased length of canal section then gives a more stable neutral pressure reservoir with which to create a pressure differential.

It also appears that the neuromast needs to be close to the canal for its benefits to be properly felt. A possible further design to experiment with would be a long canal section that was also widely spaced from the neuromast, so as to explore the effect that separation between the canal and the neuromast has on signal integrity.

An important part of this work was to determine if larger scale artificial lateral lines would still

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**Figure 3.** Sensor designs and the results from the sensor design compared to the original signal taken from in the flow behind the cylinder without a sensor present. (A) The optimised design and the comparison of the results between it and the original signal (B) the design with a square channel and the comparison of the results between it and the original signal.

**Figure 4.** Sensor designs and the results from the sensor design compared to the original signal taken from in the flow behind the cylinder without a sensor present. (A) The optimised design and the comparison of the results between it and the original signal (B) the design with a side-facing pore and the comparison of the results between it and the original signal (C) the design with a forward-facing pore and the comparison of the results between it and the original signal.
be effective at sensing flow information. As established, Reynolds numbers on the outside of the sensor are between 10 000 and 70 000; given that most fish swim with Reynolds number between $10^4 < \text{Re} < \sim 10^5$, this means that our sensor operates in a similar regime. Within the sensor, $\text{Re} = 375$. Reynolds numbers within the canals of a fish’s lateral line system can be expected to be very low given the small diameter. Previous work has measured these canals at $\sim 100 \, \mu\text{m}$ [55], which would give $\text{Re} = 2.5$ at $V = 0.0025 \, \text{m s}^{-1}$. Despite the two orders of magnitude difference between Reynolds numbers seen in this system versus in a biological system, our sensor appears to still be effective at detecting shed vortices. This is likely because while $\text{Re} < 2000$, flow is considered fully laminar, so the systems are at least comparable.

### 3.4. Sensor operational envelope

Additional simulations were run to test the effectiveness of the sensor at different speeds and with different channel diameters (figure 6). For the optimised sensor, the associated total residuals for $0.1 \, \text{m s}^{-1}$ and $1 \, \text{m s}^{-1}$ are 0.0243 and 0.0178, respectively. The result for our upper bound of $1 \, \text{m s}^{-1}$ shows only a slightly worse result than our standard speed of $0.5 \, \text{m s}^{-1}$ (0.0155). This is a positive result as it shows that the sensor is still effective for a faster underwater vehicle. The absolute upper bound at which a 10 cm diameter cylinder in water will produce a Kármán vortex street is at $3 \, \text{m s}^{-1}$, so while it is difficult to say with certainty how the sensor will behave as velocities increase, the minimal increase in residuals suggests that further increases in velocity may result in minimal increases again. More concerning is the quite significant increase in residuals that is seen at $0.1 \, \text{m s}^{-1}$ (almost 45% more error). However, looking closely at figure 6(b), it seems that the main source of this increase actually occurs due to a phase shift. At around 300 s, it is particularly evident that the two signals are 180 degrees out of phase, i.e. they are mirrored about the $x$-axis. Shifting the phase accordingly gives a new error of 0.0143, which is now better than our standard speed, and implies that the sensor will remain effective as velocities decrease, potentially even improving further. The shift in phase in an interesting result: it seems that for velocities above $0.5 \, \text{m s}^{-1}$, vortices that are shed from the same side as the sensor result in an increase in velocity for the neuromast, while vortices shed from the other side of the cylinder result in a decrease in velocity; the same is true when no sensor is present. For velocities below $0.1 \, \text{m s}^{-1}$, the opposite is true. At higher velocities, it seems that the primary mechanism is as a result of frictional forces within the water acting to drag the water within the sensor forward to cause the velocity increase, whereas at lower velocities, pressure differentials become the primary source of flow accelerations. It is also likely that as the energy within the flow decreases, the sensor itself acts to disrupt the flow more.

It has been noted that the pore size has an effect on sensitivity, with larger pore sizes giving greater responses to flow features, and so further simulations were run using the same design as the optimised sensor but with 10 and 20 mm diameter channels. The larger channel allows a larger volume of flow to move through it, resulting in a greater response to external stimuli. We theorise that at high velocities, the larger volume of water in the sensor will become more susceptible to noise due to the higher energy in the system, while the opposite will be true at lower velocities.
velocities. A narrow channel is predicted to show a smaller response to flow stimuli, but, in contrast to the wide channel, will be less susceptible to noise in high velocity background flow. In the slow background flow, the response is expected to be minimal, to the point that it might not be possible to correctly capture the signal from the flow.

It is first of all interesting to note that there are no cases where either larger or smaller diameter sensor display better signal similarity (figure 6). This seems to indicate that a 15 mm canal offers an optimal balance between reducing noise and increasing sensitivity. In the 1 m s$^{-1}$ velocity flow, it seems to be the case that the narrow channel (g) is more similar to the desired result than the wide channel (i), as predicted; this is most evident towards the end of the series. At 0.5 m s$^{-1}$, however, both canals result in noisy detected signals (d) and (f), with the narrow canal faring slightly better. At 0.1 m s$^{-1}$, the two canals have very similar errors (a) and (c), again apparently noisy. As seen in the previous set of results, there are periods here in a number of the results where the detected and expected signal appear to be 180 degrees out of phase, particularly clear in figures 6(a) and (i). Shifting these, along with figures 6(c) and (f), errors are now seen to be 0.0188 for the narrow design at 0.1 m s$^{-1}$ and 0.0193, 0.0185, and 0.0207 for the wide design at 0.1, 0.5 and 1 m s$^{-1}$ respectively. This marks a reduction in residual error for all cases except the 20 mm canal at 1 m s$^{-1}$. If we maintain the observation above that the out of phase response is as a result of pressure differentials while the in phase response is due to flow velocity and associated frictional forces, we can note that the narrow canal is better at low velocity, likely due again to the smaller volume of water that need move to illicit a neuromast response. The wide canal appears to be less effective at low velocity for the same reasoning, as at lower background flow velocity, the detected signal amplitude is markedly less than for the narrow canal. As flow velocities increase, in the narrow canal there seems to be a definite switch between pressure differential and friction forces as the driving mechanism, while the wider canal seems to be subject to both, leading to the increased noise in the detected signal.

3.5. Physical sensor proof of concept
A prototype of the sensor was demonstrated in a static container of water. Figures 7(a)–(c) shows the sensor
moving through the water, using a ruler to highlight the distance covered, without displaying the signal on the neuromast. This result is as expected, as our rear-facing pores act to filter out the background flow or in this case, filter out the inertial effect of the static water.

Figures 7(d)–(g) shows the sensor immobile with the cylinder moving through the container and generating a vortex as it passes; this is seen by the recorded oscillation. Figure 7(f) shows the most deflection; it is also possible to see the vortex forming close to the mouth of the sensor in the ripples of the water. This panel is most similar to the setup used in the simulation, so the correlating results lend support to one another.

Figure 8 shows the results of the sensor when tested within the flow tank. The sensor was placed at six different locations and the displacement of the visual tracker was measured during each run. All locations were chosen to be on one side of the flow tank, with two positions at the midline of the cylinder, 2 at 80% of the cylinder diameter (predicted to be the position of maximum variance [50]) and 2 at twice this distance in a region where vortices are predicted to have minimal effect, for these three positions, one is taken at 10 cm from the cylinder and the other at 20 cm to investigate the effectiveness of the sensor at detecting vortices as they degrade with distance from source. Three trials were done at each location to increase validity of results and these are shown in the different lines on the graphs at each location. It can be seen that the sensor shows deflection in response to the formation and shedding of vortices in all of the sampled area.

We see the best consistency between trials in the centre of the row closer to the cylinder (XiY1, XiY2 & XiY3), which is the position that the simulations have predicted to be the best spot for the sensor to operate in. We also see the least deflection in the first row at the furthest y position (XiY3) from the cylinder, which is also predicted by simulation, due to the vortex forming in the region behind the cylinder and then being shed downstream from there. XiY3
Figure 8. Results of the sensor when positioned within the experimental tank in each of the positions marked by the red circles in figure 1. The letter label of each graph corresponds to the data taken when the sensor was at that position. (A) Results from position (a) (B) results from position (b) (C) results from position (c) (D) results from position (d) (E) results from position (e) (F) results from position (f). In each graph, a single vortex is being detected, with the starting time occurring when water levels reach a given level within the tank; this is done to make comparisons easier. Prior simulations have suggested that (B) and (E) should give the greatest variation, and across the three results, we see the best consistency here. However, (D) actually shows the greatest deflection in one of the trials. Due to the complex nature of fluid dynamics and the variation in starting conditions present in the experimental set-up, it is unsurprising that the maximum deflection is not always in the position of greatest variation.

is further from the vortex than the other positions, hence the reduced deflection.

An interesting result to note is the difference in time when the deflection occurs that can be seen in multiple positions. This is most likely to be as a result of the vortex forming and being shed from different sides of the cylinder in different trials. This is corroborated by the fact that the later deflections tend to be reduced. The vortices shed on the far side of the cylinder are further from the sensor and also must travel further downstream before they can be detected, explaining the slight delay and indicating that the earlier troughs are likely from vortices shed on the sensor side of the cylinder, while the later troughs are from the opposite side. It is also possible that the body of the sensor is interfering, as some of it does sit in the path of the shed vortices and this could also cause both a delay and a reduced deflection.

Overall, these results indicate that the sensor is able to detect shed vortices in flow, and over a wider area than initially thought.

4. Conclusion

Our new optimised artificial line sensor design (figure 1) has been shown to be effective at detecting vortices shed by potential obstacles or upstream robots. We also explain and evidence our rationale behind the design choices, all of which can be rooted in biology, with a series of simulations where the particular traits we want to emphasise are removed to demonstrate an associated decrease in performance. In every case, we see significant increases in residuals and loss of similarity in signal shape. To validate simulated results in reality, we produce and test the proposed sensor and show that it is able to filter water flow caused by the sensor motion in water, and sense vortices shed by both a passing cylinder in static water and vortices shed behind a cylinder in flow. This sensor offers an alternative sensory suite that is both inexpensive and simple to manufacture that could be easily integrated onto pre-existing underwater robotic platform used to inspect underwater structures, explore canals, or perform environmental monitoring. It also offers the potential for an artificial lateral line system that is effective using only a single sensor, which could result in significant reductions in complexity and expense. Such a reduction could be exploited for swarming, to create large numbers of simple and inexpensive robots that use this artificial lateral line system to navigate and interact with each other, and in turn display complex emergent behaviours. We have already began to work towards this goal on both software and hardware fronts for example training a neural to read the flow fields behind a cylinder in simulation, and from this navigating said flow field to a given location by sampling only a single point per unit time. This is now being further developed into a multi agent model. A simple bio-inspired robotic fish with a compliant caudal fin has also been designed to host our optimised artificial
lateral line sensor, that once completed will mark the beginnings of the development of the large scale swarm just mentioned.

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Data availability statement

All data and code used for this paper can be made available upon reasonable request.

Author contribution

ES built the simulations and analysed the results. SH supervised the project and contributed to analysis.

Conflict of interest

The authors have no competing interests.

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