Underwater Bioinspired Sensing: New Opportunities to Improve Environmental Monitoring

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Smart environmental monitoring networks are a growing part of the Internet of Things (IoT). They are useful to detect, forecast and assess human impacts on the environment as well as the effects of climate change on society. As climate uncertainty grows, we will increasingly rely on these networks to address significant societal challenges including the reduction of available drinking water, diminished agricultural productivity and growing threats posed by extreme weather events on human health and safety. Bioinspired designs can lead to a new generation of devices to ensure that environmental monitoring networks remain accurate and reliable over a wide range of physical conditions. The Instrumentation and Measurement (IM) community is responsible for measuring, detecting, monitoring and recording a vast range of physical phenomena. As such, IM researchers should lead the development of new types of standardized bioinspired sensors which can be integrated into the highly valuable and urgently needed IoT-based environmental monitoring networks of the future. As an example, we show how fish-like underwater bioinspired sensing can improve both the effectiveness and efficiency of monitoring upstream migration.

The first environmental monitoring systems were the ancient rituals and stories of the pre-mechanical age from 3000 BC to 1450 AD, used to track the movement of animal herds and changes in the length of the day [1]. During the mechanical age, from 1450 to 1840, conflicts between societies related to the overuse of forests, streams and grazing areas for livestock created the need for environmental monitoring and management. The eletromechanical age, from 1840 to 1940, experienced the emergence of nation-states, leading to governmental agencies tasked to protect natural resources and punish polluters. The first technical environmental monitoring systems were rapidly adopted in the 1960s by the water supply and wastewater sectors using supervisory control and data acquisition (SCADA) technologies.

Today, in the electronic age (1940–present) we are experiencing the fourth industrial revolution. Environmental monitoring systems now consist of sensors interconnected through a mesh of networks with the capability to interact and exchange data via the IoT. In addition to sensor-based monitoring, these networks include separate layers for data exchange, processing and reporting. IM researchers are leading the development of a new generation of devices and methods to provide scalable and dependable environmental monitoring technologies [2]. These technologies are now expanding far beyond their SCADA-based roots. Current trends include the increasing use of remote sensing, autonomous robots and animal-borne biosensors to collect environmental data. To address the challenges imposed by the wide variety of data sources, Geographic information system (GIS) software has been developed. GIS-based reporting allows researchers and managers to combine and assess environmental and anthropogenic data together. The results are used for local, regional and global resource assessment and management. Future environmental monitoring systems are expected to continue to expand, including new sources based on technologies with increasing compatibility with living organisms. A graphical overview of the past, present and future of technical environmental monitoring is illustrated in Fig. 1.

In the past, technical environmental monitoring consisted of single sensors which uploaded data in a one-way exchange from CPUs to a central data warehouse. Data were processed and then viewed using GIS software. The results were mapped and evaluated, most commonly used in reports on disaster management, planning and forecasting. Due to rapid advances in the IM and IT sectors, present technical environmental monitoring is IoT-based and dynamic, allowing for real-time processing of more complex tasks including climate resilience and adaptive management. With the help of machine learning, automated and personalized reporting is now possible. The future of technical environmental monitoring

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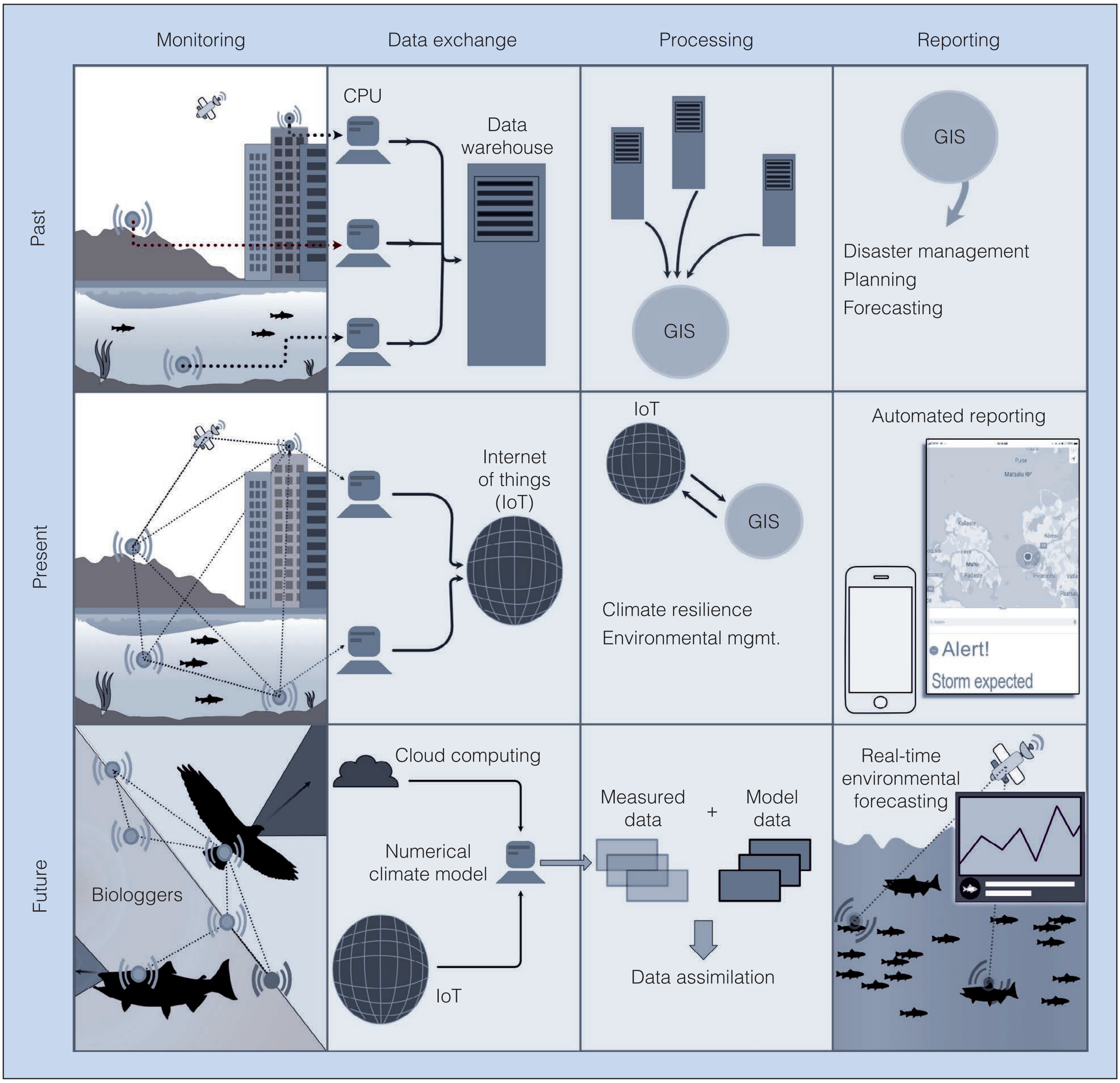

Fig. 1. Conceptual overview of the past, present and future of technical environmental monitoring, data exchange, processing and reporting.

will go beyond observations of the physical environment to include living organisms and their interactions within it. Data will be fused with models to create assimilated "virtual twins" which will allow for real-time forecasting at the population and individual levels.

Environmental monitoring encompasses the spatial and temporal changes in land, water, air, biological, noise, socio-economic and health and safety data sets. There is a rapidly increasing demand for environmental management reporting, ranging from real-time air pollution alerts in cities to annual forecasts of fish stocks in our oceans. Environmental managers rely on these reports to plan mitigation actions which reduce the adverse impacts of human activity on the environment over the long-term. However, an opposing trend in the form of climate resilience now rapidly emerging. Climate resilience uses environmental monitoring data to reduce the negative impacts of environmental change on human society. Research and development by the IM community is therefore at the frontiers of traditional environmental management as well as climate resilience. For example, it is now possible to use cloud computing to automatically generate up-to-date environmental reports using smart sensors connected to the IoT [3]. Ultimately, automated environmental reporting will emerge which makes use of multisensory data fusion from environmental data streams. An example environmental data fusion model using assimilation with numerical climate models and machine learning to improve management reporting is summarized in Fig. 2.

The IoT in its current form encompasses consumer, commercial and industrial categories. Increasingly, sensors for

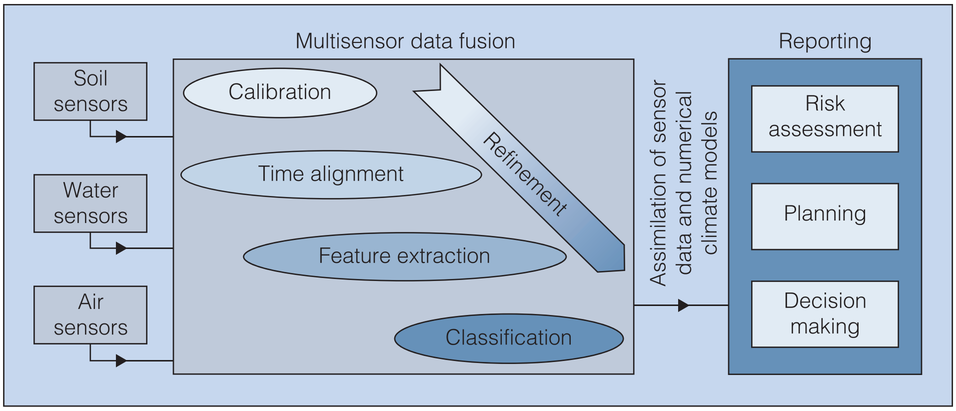

Fig. 2. Block diagram of environmental monitoring sensor fusion and reporting, adapted from [4].

environmental monitoring are being added with architectures similar to other dynamic, spatially distributed systems such as smart cities and smart ports [5]. The technical requirements for sensing, communications, computing and storage between smart environments are largely based on their predefined objectives. The main objectives of smart environmental monitoring are to detect, forecast and assess the impacts of environmental change on human society. Fortunately, Nature has evolved a host of biological environmental sensing specialists.

Why We Should Look to Bioinspired Sensor Designs

The Earth's natural environment includes a wide variation of temperatures, ranging from minus 89.2 °C to 70 °C and pressures from 8.87 m H2O to 10,994 m H2O. Biological organisms face the additional challenge of energy harvesting and storage, often with limited mobility. Because of these challenges, Earth's organisms have evolved and developed advanced, robust sensing capabilities. Their ability to evolve and thrive under a wide range of harsh environments makes them ideal candidates for bioinspired sensor designs. Specifically, we believe that bioinspired sensors can provide exciting new opportunities for improving environmental monitoring. Bioinspired designs are based on processes, materials and devices inspired by biological evolution. The environmental monitoring systems of the future should also sustainably coexist with biological systems and are therefore ideally biodegradable and biocompatible. Indeed, well-known conventional technologies which collect energy, sense and compute all have existing bioinspired equivalents: edible solar cells as technological surrogates for green leaves, high-resolution cameras can be replaced with eyes, and brains can be viewed as nothing more than biodegradable computers [6]. Because bioinspired designs are driven by evolution, they are both robust and highly tuned to a wide range of environmental conditions. As shown in Table 1, these conditions can be grouped into three types of environments: soil, water and air, based on their fundamental physical differences.

Upon performing a comparison between the relative costs and impacts of soil, water and air, it becomes clear that water is currently the most important type of environment to monitor. This is because water is fundamental to all ecological processes and has the highest relative cost when monitoring is considered. As a result of this, we focus our attention on the challenges and opportunities related to bioinspired underwater sensing as they relate to environmental monitoring. One successful example is based on fish-like artificial lateral lines, which can be used to autonomously classify complex

Table 1 – Comparison of environmental monitoring types, based on physical conditions.

Type	Relative Cost to Remediate	Parameters	Level of Global Standardization	Impacts
Soil	$$$	Soil chemistry, water and gas content, carbon, biodiversity and physical properties	Medium: most countries have regulations in place, international commitments exist	Wood and food production, transportation, carbon storage and biodiversity
Water	$$$$	Physiochemical water quality, nutrients, pollutants and biodiversity, river discharge	High: nearly all countries have regulations, thresholds are known and international commitments are well-established	Water supply, food and energy production, shipping and transportation, cooling and heating, carbon storage and biodiversity
Air	$$	Particulates, gasses and chemical compounds, air circulation	Medium: some countries have regulations, thresholds for some parameters follow international commitments	Combustion for energy and food production, transportation, carbon storage, human and animal health

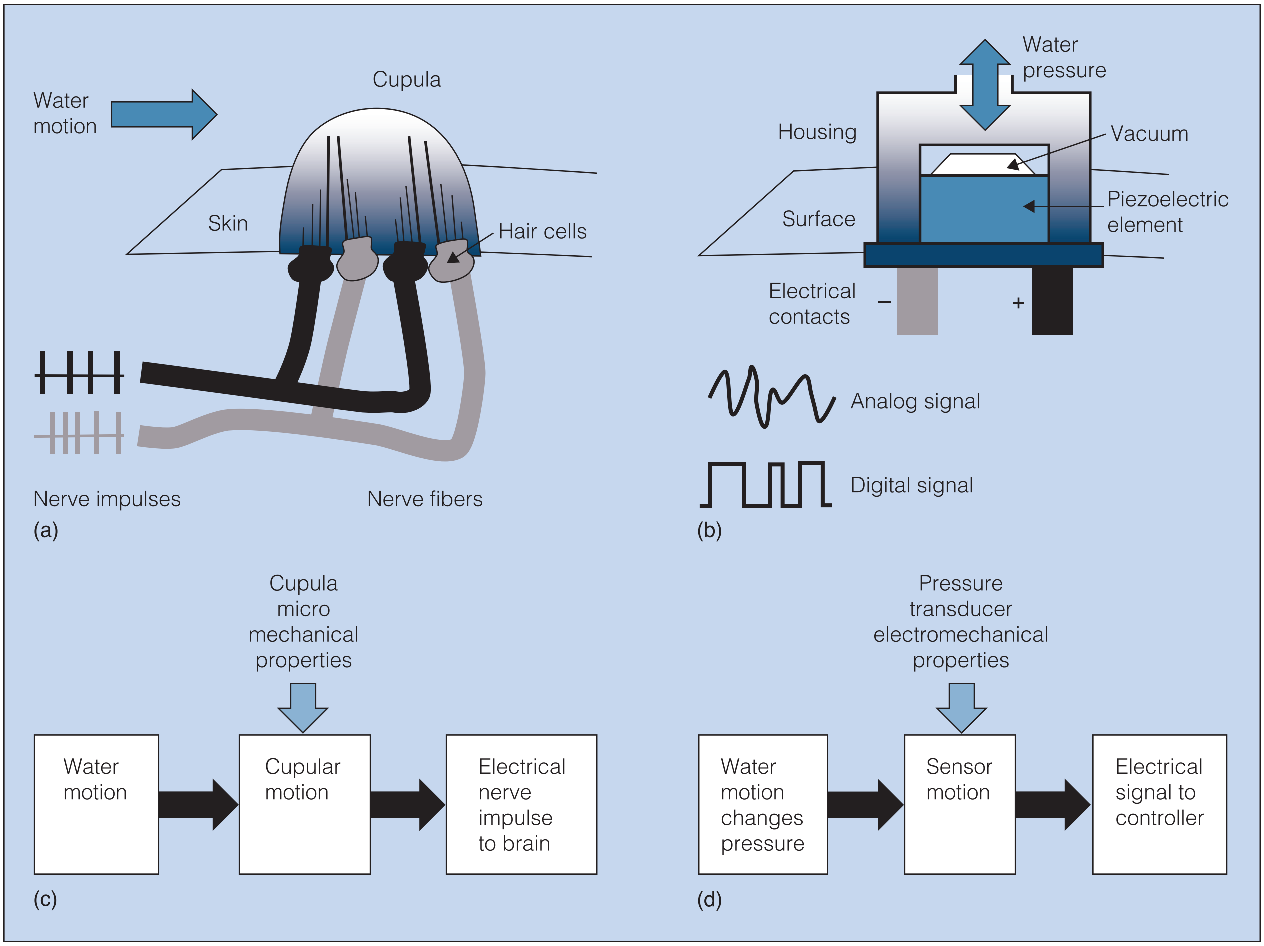

Fig. 3. Side-by-side comparison of biological and electronic pressure sensors. (a) The neuromast is a biological water pressure sensor, consisting of a gelatinous cupula and hair cells whose movement are transmitted as nerve impulses along the afferent nerve fibers [7]. (b) Schematic of a standard piezoelectric water pressure sensor, which translates water depth and motion into analog or digital signals. (c) Biological underwater stimulus pathway in which water motion and the mechanical properties of the cupula are translated into electrical nerve impulses sent to a fish's brain. (d) Similar to their biological counterparts, electromechanical pressure sensors respond to water pressure changes, sending electrical signals to a computer or embedded microcontroller.

flows that help or hinder upstream and downstream migrating fish.

Fish experience the flow around their bodies via a bimodal sensory system consisting of the inner-ear and lateral line organs. Similar to an electronic inertial measurement unit, the inner ear senses the linear and angular accelerations of the body. The lateral line organ is made up of several arrays of neuromasts, which cover the head and run along the body and are velocity and pressure sensitive. Each neuromast is made up of a gel-filled cupula which bends depending on the local motion of the water passing over the fish's body. Pressure-sensitive neuromasts are embedded in the fish's skin in tiny canals, connected via pores to the surrounding flow. In most fish species, they are primarily used as high-frequency (50-200 Hz) flow detectors. Bioinspired artificial lateral lines can be created using an array of underwater pressure sensors. A side-by-side comparison of a biological neuromast with conventional piezoelectric pressure sensor is shown in Fig. 3.

The robust flow sensing ability of the biological lateral line has inspired researchers to develop a wide spectrum of artificial sensing organs. Current approaches include piezoelectric, capacitive, thermal and optical sensors. Although the majority of research and development remains constrained to laboratory studies, commercial implementations using artificial lateral lines are foreseen which can expand flow sensing abilities, leading to new methods to measure and explore the underwater environment. Current variants of pressure-sensing artificial lateral lines are even capable of flow velocity and turbulence parameter estimation on par with a state-of-the-art acoustic Doppler velocimeter [8].

Example of Bioinspired Sensing to Improve Environmental Monitoring: Fish-like Artificial Lateral Lines

Freshwater ecosystems around the world are in decline, and fish are especially vulnerable. Fish are excellent indicators of ecosystem health because they have evolved for specific roles in their environment. In Europe, the major long-term threats facing fish populations are river regulation, loss of habitat and barriers to free migration. To address these threats, bypass structures around river barriers, called fishways, are built. Ideally, fishways ensure access to habitats by allowing upstream

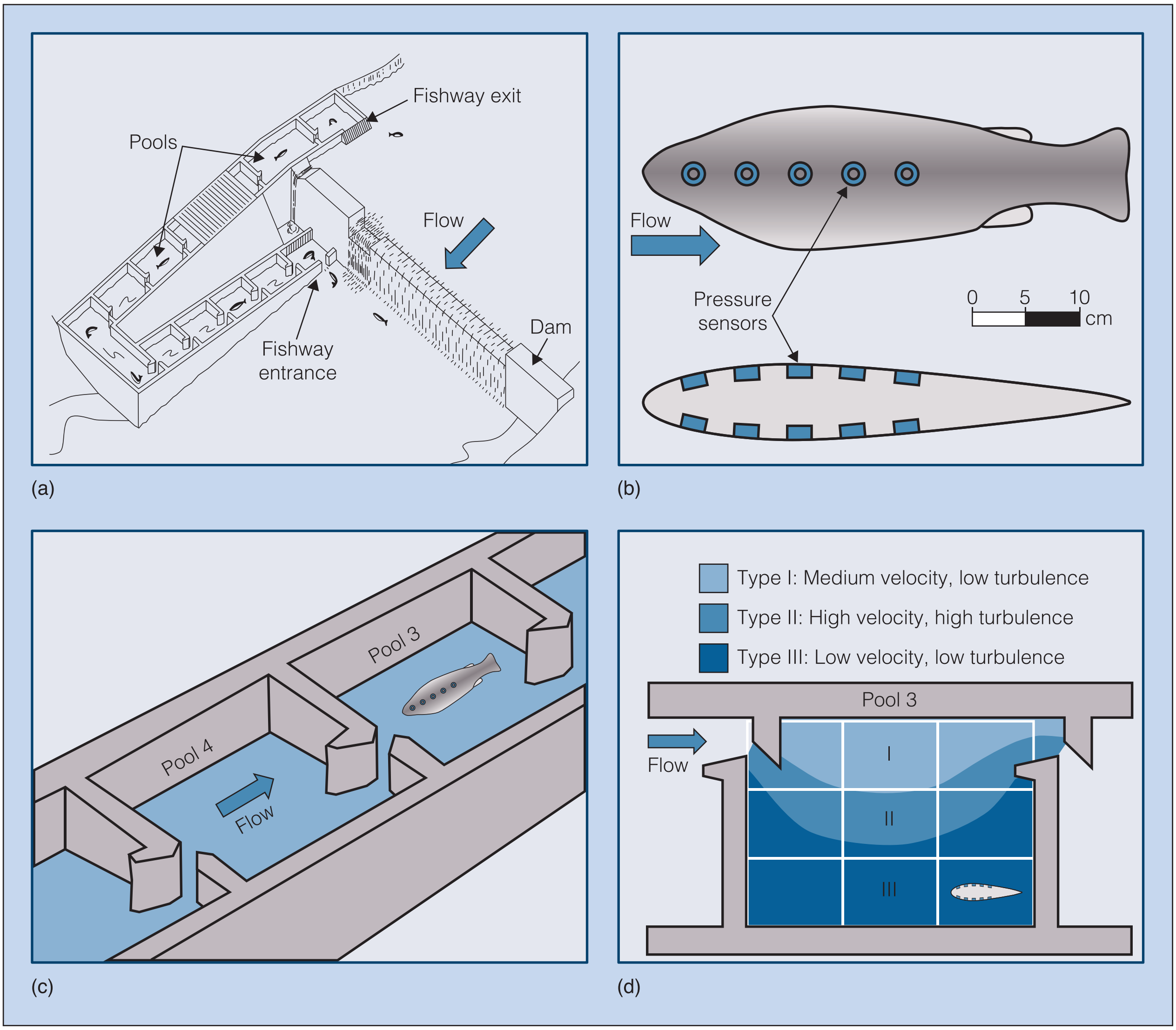

Fig. 4. Using a bioinspired artificial lateral line to monitor fishway effectiveness. (a) Fishways are structures consisting of a series of pools to aid upstream migrating fish around dams, after [9]. (b) An artificial lateral line probe consists of a fish-shaped body outfitted with two arrays of pressure sensors. (c) The probe is placed at different pool locations and records body-oriented pressure fluctuations. (d) The results of the bioinspired sensor are the autonomous spatial classification of three distinct flow types, which are known to be preferred or avoided by fish during upstream migration. This is in contrast to conventional, point-based measurements which rely on expert judgement and do not take the sensing abilities of fish into account.

migration around barriers, especially during the spawning season. Unfortunately, experience has shown that building a fishway does not guarantee successful passage. After spending billions of Euro on building fishways, the international knowledge gathered over the last 40 years has led to regulations and guidelines providing specific technical requirements for fishways. To satisfy these regulations, fishway monitoring has become an international commercial enterprise. A wide range of monitoring technologies are deployed, including acoustic velocity probes, infrared scanners, and SONAR imaging.

Current fishway monitoring technologies are largely limited to measurements of static, time-averaged flow fields. Due to the lack of time-varying data, maps of the flow velocity from pool to pool are created using static point measurements or numerical models. The maps relate the flow velocity and turbulence to observations of fish migration efficiency from laboratory and field investigations. The mapping procedure requires expensive equipment and cumbersome measurements as well as significant post-processing. In order to improve fishway monitoring, a bioinspired artificial lateral line probe was developed. The probe is outfitted with an array of pressure transducers which captures changes in the flow acting over a fish-shaped body. Machine learning algorithms perform unsupervised classification using the pressure data. Compared to the state-of-the-art, this provides a more accurate and efficient mapping system for real-world flows encountered during fishway monitoring. A graphical depiction of the bioinspired fishway monitoring process is shown in Fig. 4.

Challenges

In stark contrast to conventional land-based sensors, underwater devices must withstand large pressures, water intrusion,

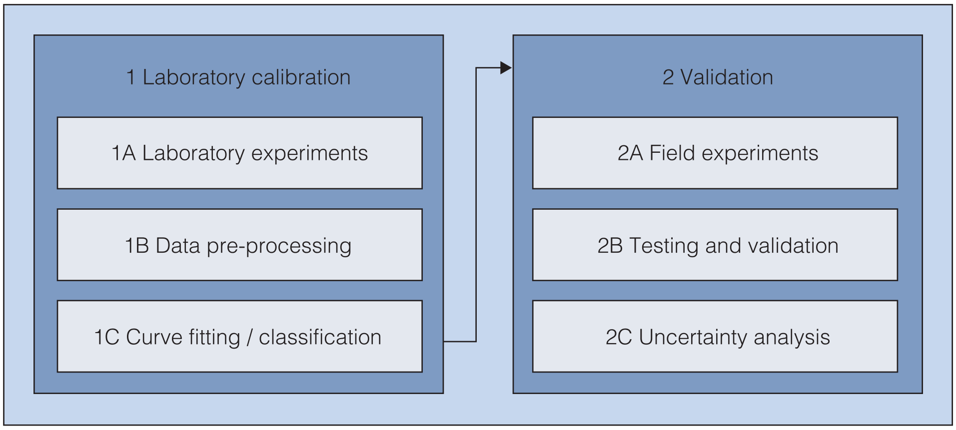

Fig. 5. A simple, two-step procedure for ensuring that bioinspired sensor performance is adequate for inclusion in existing environmental monitoring systems, based on detailed analysis found in [16].

biofouling and limited communications. This has the unfortunate result that the costs of existing stationary underwater sensors and animal-borne biologgers are already considerably higher than their land-based counterparts. A new generation of underwater bioinspired devices will need to make use of new materials for robust sensing and communications. Additionally, a major challenge to the success of bioinspired sensing is the significant and undervalued threat posed by the lack of standardization. Above all, the standardization challenge hinders technological scalability. This is because integrating large numbers of new and largely novel data streams can place a significant burden on available communications bandwidth and requires considerable signal processing. Recent advances include biodegradable and biocompatible pressure sensors [10] and implantable antennas [11] as promising bioinspired alternatives to conventional devices but will require comprehensive testing before they will be accepted by industry as part of IoT-enabled environmental monitoring systems. To address the standardization challenge, the IEEE Standards Association is undoubtedly the best-suited candidate to address this challenge due to their longstanding experience in developing and implementing global technology standards. In addition, we suggest that the IM community is well-posed to develop environmental monitoring communications standards, akin to those for medical device communications and computerized healthcare systems [12].

To partially address the standards challenge at the research and development stage, we have adopted a simple two-step procedure for the calibration and validation of new bioinspired sensors based on our own experiences developing the artificial lateral line probe [8], presented in Fig. 5. The first step involves the familiar procedures for laboratory calibration: experimentation under controlled conditions followed by data pre-processing (e.g., outlier removal, band pass filtering) and finally curve fitting and classification. Because bioinspired devices are often multisource, they are especially well-suited for classification. Therefore, laboratory calibration activities may also require traditional data fusion using Dempster-Shafer theory [13] as well as newer, machine learning approaches such as deep learning [14]. The second step requires the additional effort required to collect real-world data for testing and validation of the fit curves and classification results. These results are then used to conduct an uncertainty analysis of the new bioinspired technology. This is critical because implementing cost-effective solutions for environmental monitoring in the underwater environment requires especially reliable designs [15].

Conclusion

The IM community is responsible for measuring, detecting, monitoring and recording a vast range of physical phenomena. In addition to these observational activities come the responsibilities of calibration, uncertainty analysis and the development of data processing tools and applications for environmental monitoring.

The main objectives of smart environmental monitoring are to detect, forecast and assess the impacts of environmental change on human society. As the uncertainty in our environment grows, we will increasingly rely on these networks to address environmental challenges to societal well-being. We propose that bioinspired underwater sensors can provide new and effective means to explore, detect and monitor the Earth's rivers, lakes, seas and oceans. To achieve this, the IM community should lead the way in developing new types of standardized sensors which can be integrated into rapidly developing IoT-based environmental monitoring sensor networks.

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