

Development of current sensors for digitizing expert knowledge in fish feeding towards sustainable aquaculture

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Abstract

Improving the efficiency of fish feeding contributes to achieving sustainable expansion of the aquaculture industry. However, expert knowledge on feeding remains reliant on experience. This paper presents a new approach of digitizing such knowledge by measuring underwater currents induced by fishes as indicator of their behavior and appetite. A prototype current sensor suite was constructed to measure the current around the fish cage, especially during feeding.

Keywords: aquaculture, fish feeding, underwater currents, current sensors

1. Introduction

While seafood consumption has been increasing every year, capture fisheries production, facing issues of overfishing, has remained static with slight fluctuations in the past decades. Since early 1990s, the aquaculture industry has been expanding consistently to meet the rising demand worldwide, making up 46% of the global production in 2018.¹

The problem arises in the industry's sustainability. Unsustainable management of fish farms not only poses a threat to their surrounding aquatic environment but also to the health of the fish stocks.^{2,3,4} One crucial issue is the need for efficient feeding decision-making. Poorly timed and excessive feeding leads to poor cost-efficiency in raising fish.⁵ Worse, it produces uneaten feeds that decompose at the bottom, contributing to the decline of water quality in the surrounding environment.⁶ Such

threat leads to slower growth rates, poorer quality of harvest, or at worst, massive fish kills.^{6,7,8} Fish farmers incur losses in their operations as a result.^{3,5,6}

Efficient feeding has usually been achieved with a decision made by an expert farmer. There is a significant difference in the quality of the harvested fish fed based on expert and non-expert decisions. Such decision making remains to be an "art," where prediction is still intuitive, subject to the expert's experience, and unquantifiable by a unified standard.^{9,10}

Digitization of experts' knowledge may help non-experts improve their feeding decisions, which will not only improve the amount and quality of their harvest, which will not only consequently increase their income, but will also increase the supply of high-quality seafood, lower their prices, and at the same time minimize pollution in the farm environment.

Current research efforts on this problem focused on the measurement of fish behavior through machine vision and water quality changes using sensors as input parameters into machine learning models to make a feeding decision.^{5,10,11} So far, experiments in these works were performed in intensive farms where environmental factors were controlled. No research work performed in open environments, i.e. extensive farms, have been found so far.

This paper explores a new approach on digitizing expert feeding knowledge in tuna farms in aquatic environments. In this approach, velocities of underwater currents induced by the movement of fishes inside a cage will be measured and their relationship to the behavior and appetite of the fish inside will be investigated. While presenting the sensor system's overall architecture, this paper focuses on the design of a prototype sensor for initial current measurements and on its ongoing development.

2. Sensor System Architecture

In this system, a network of sensor nodes is placed around a 40-meter diameter fish cage with depth of 20 meters. Each node consists of multiple current sensors measuring current velocities for every 1-meter depth. In

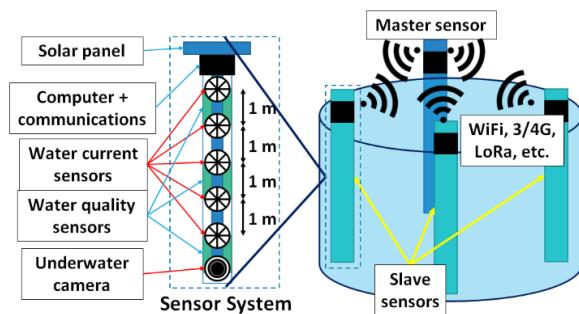


Fig. 1. System architecture for monitoring fish appetite and water quality in a fish cage

addition to measuring currents, it also has water quality sensors (dissolved oxygen, temperature, conductivity, pH, etc.) at multiple depths. An underwater camera is placed to observe the fish movements, especially during feeding. Each node is designed to have a capacity for energy-harvesting— solar, wind, tidal, or other sources — so that it can operate continuously off-grid. A computer above surface performs corresponding calculations on

the sensor readings to obtain the measurements, timestamps them, and stores them internally.

These sensor nodes communicate in a star network, where one node is designated as the master and the rest as slaves. Slaves send their measurement data to the master, which also collects its own measurements. Data aggregated by the master node may either be collected by the farmer onsite or be transmitted directly to a data center. Communication technology to be used — WiFi, 3G, 4G, LoRa, etc. — will be configured accordingly to implement this network architecture.

Initial data collection is to be made in a fish farm, where underwater currents are to be measured near cages at depths with fish presence, especially during feeding times. This is to provide insight for validating or in improving the proposed design.

3. Sensor Suite for Initial Measurements

3.1. Sensor suite system design

For the initial measurements, two custom-built current speed loggers are mounted on a metal frame at two different depths at which fishes are observed before, during, and after feeding. These sensors measure only

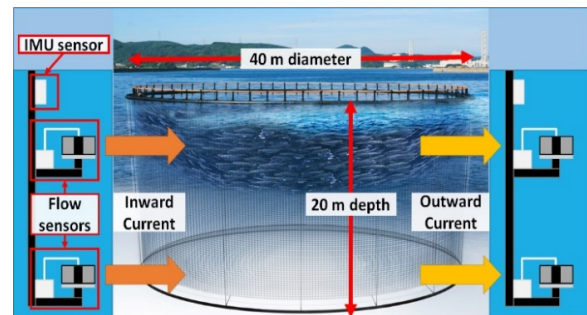


Fig. 2. Design of the initial farm experiment using the prototype sensor suite consisting of flow and IMU sensors

one flow axis given their fixed mounting. An inertial measurement unit (IMU) sensor is mounted closest to the current sensor of interest. This will measure movement of the frame caused by fish-induced currents. These sensors are remotely triggered by Bluetooth to start logging measurements before they are placed underwater for hours.

Ideally, at least two sets of sensor units should be deployed so that the other will measure the current going towards the fish cage, which will be cancelled from the

outgoing current. Due to time constraints, however, one set will be used for the initial measurement. Two or more sets will be deployed for the next measurement campaigns.

3.2. Custom-built current sensor

3.2.1. Components and operation

Since initial measurements will be performed, it was decided to use a low-cost current sensor. The sensor developed for this experiment is a modified propeller-type flow sensor intended for measuring water flow through water pipes. Its Hall-effect sensor generates

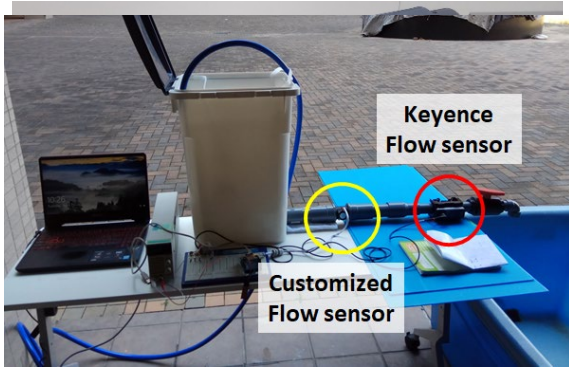


Fig. 3. Calibration test setup of the current sensor where it is connected to a digital flow sensor as they both measure water flow from the container.

pulses proportional to the magnetic propeller's rotation. An Arduino microcontroller counts these pulses for a given period, obtains the average frequency throughout the period, and then calculates the current speed using a calibration coefficient. It then adds timestamping to the reading and stores it in a microSD card with its datalogging shield with SD and RTC capability. A Bluetooth module is also connected so it can be triggered remotely by a computer to start and stop measurements. The current sensor is powered by a 9-volt supply (six AA batteries in series) with a capacity of 2700 mAh. A power endurance test was made by allowing it to operate continuously while being powered by the batteries. Result showed that it can collect measurements reliably for around 22 hours.

The flow sensor was not originally designed to be waterproof and reinforcements were therefore made by

permanently sealing its electronics enclosure and by replacing its original cable with a waterproof rubber molded cable. Other unit components are housed in an IP68 enclosure.

The mounting is a 12-meter aluminum structure with four legs to which the sensors are attached to. The sensors depth can be adjusted by sliding them through the legs. Each leg is made of three four-meter frames. Cross-like reinforcements are attached at the leg joints to minimize

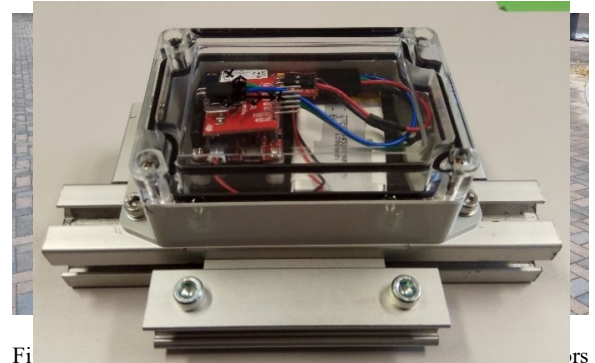


Fig. 3. IMU sensor enclosed in its waterproof box with its aluminum attachment to the frame

bending and to enable the mounting to withstand the underwater currents.

3.2.2. Flow sensor cross calibration

For accurate measurements, the developed flow sensor was cross-calibrated with a digital clamp-on type flow sensor (Keyence FD-Q32C). Both sensors were connected to an elevated water source where flow was partially controlled, as velocity and flow rate were dependent on the height, and subsequently the volume, of the water in the container.

Calibration is done by correlating the pulse frequency to the speed of water through the custom sensor, which is calculated by measuring the flow rate through the digital sensor. This is calculated using the relationship between the flow rate and speed of a fluid through a pipe and the continuity equation, which given in the following equation:

$$v_F = \frac{v_{DF} A_{DF}}{A_F} = \left(\frac{q_{DF}}{A_F} \right) \left(\frac{1000}{60} \right) \quad (1)$$

In this equation, v is the water speed, A is the cross-section area of the sensor pipe, and q is the flow rate. Subscripts F and DF denote the custom and the digital sensors, respectively. Regardless of the difference of the cross-section areas of the two sensors, that of the digital sensor is cancelled out in the equation. The constant at the right converts the units from flow rate (L/min) to speed (cm/s).

To select the best averaging period to be used in measurements, three periods were selected for calibration – 1, 5, and 10 seconds. Readings at 1 second were found to be discrete as the microcontroller count discrete number of pulses per second. Range of readings from the digital sensor are classified as the discrete readings from the custom sensor. Readings using the 10-second configuration were more continuous. However, there are higher chances of averaging high and low sample values, which may not properly represent the actual measurement. Using the 5-second period seems to be a favorable configuration as there are smaller chances of samples with large differences, while its readings are still continuous. This is therefore the selected configuration for the upcoming experiments.

3.3. IMU water movement sensor

The core component of this sensor is the Sparkfun 9DoF Razor IMU M0, a very compact microcontroller with an MPU-9250 IMU and a μ SD card slot onboard. Its IMU consists of accelerometer, gyroscope, and magnetometer sensors, and is therefore capable of measuring linear acceleration, angular rotation velocity, and magnetic field vectors. With a Real-Time Clock (RTC) attached, this board can timestamp its measurements before writing them to an μ SD card. Powered by a 1000-mAh lithium-ion polymer (Li-Po) battery, it is enclosed in an IP68 enclosure. Power endurance test result showed that this sensor can collect data for around 22 hours as well.

4. Trial river measurements

While waiting for the plans of the initial fish farm experiment to be finalized, we decided to perform current measurements with the constructed sensors along two rivers in the northern part of Fukuoka. The first measurement was along Onga River (遠賀川), one of the longest rivers in Kyushu island. Its width and depth at the point of measurement is around 290 and 1.6 meters,

respectively. The second measurement was along Nishi River (西川), a small river connected to the northwestern end of Onga River, where the width and depth at the measurement point is around 75 and 1.3 meters, respectively. Due to the shallow depths, only one 4-meter frame segment was used. Currents at the bottom and near surface of both rivers were measured, with the heights of the upper sensor were adjusted accordingly. The IMU sensor was placed in proximity to the bottom current sensor. Measurements at each river were taken for around 30 minutes.

Save for two data points for each depth ranging from 0.75 to 2.26 cm/s, the currents sensor readings along Onga River were at 0 cm/s. More non-zero sensor readings were collected at Nishi River, with the measurement at the surface peaking to 18.8 cm/s. On the other hand, almost all readings at the bottom of this river is at zero, except for a few instances peaking at 3.76 cm/s. No significant changes were observed in the accelerometer and gyroscope readings since the frame was settled at the riverbed. Any changes observed was attributed to lack of calibration as well as human intervention.

It was expected for Onga river's current to be slow because of its large width. However, visual observations suggest that there still were small movements by the water, as seen from the waves at the surface. This may indicate that the flow sensor could not detect those small currents, reading them as 0 cm/s.

For better results in future measurements, we will calibrate the sensors' pulse readings for each measurement to the readings of a calibrated digital sensor. Doing this can verify whether the custom sensors can detect small currents or not. In addition, we are considering attaching a funnel at the inlet of the current sensors. This will amplify small currents entering the sensor, which will then use its measured current to calculate for the current at the funnel inlet.

5. Conclusion and future work

This paper presents the ongoing development of a prototype sensor suite, consisting of modified flow for measuring water currents induced by fish movement. Flow sensors were modified and recalibrated to measure underwater currents. The IMU sensor was also developed for measuring movement of the mounting frame. Both the current sensors and the IMU sensor can record current measurements reliably for at least 22 hours.

As the mounting frame has been completed, the sensor suite is ready to be deployed in the fish farm for the initial measurements, which will be performed within the next few weeks. Trial measurements have been made along two rivers in Fukuoka, showing A second sensor suite will also be constructed after the first experiment. The

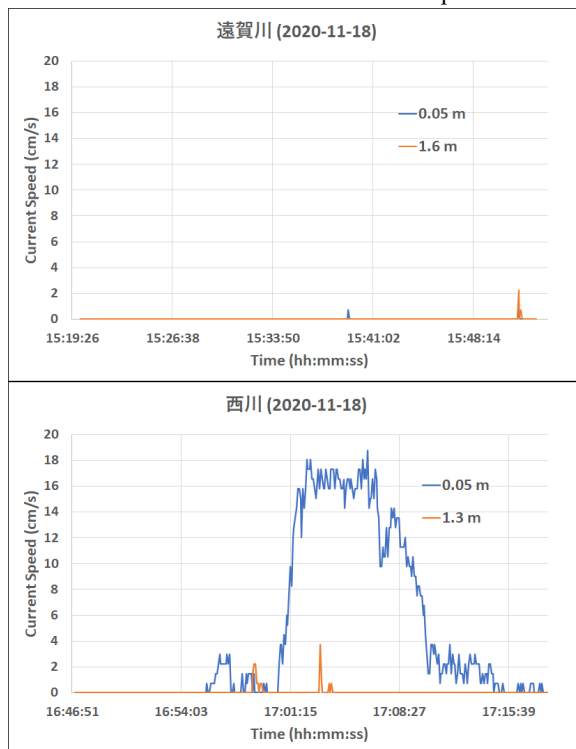


Fig. 3. Current sensor readings at both depths at Onga River were very low, while larger readings were measured at the near surface of Nishi River.

relation of current measurements from the experiments with the fish behavior during feeding will be analyzed. Future work also includes development of a networks of sensor nodes as described in the system architecture using more robust current sensors. These are future

research tasks towards digitizing expert knowledge in fish feeding in aquaculture farms.

References

1. FAO: The State of World Fisheries and Aquaculture 2020. In brief. Sustainability in action, FAO, 2020.
2. R. S. S. Wu, "The environmental impact of marine fish culture: towards a sustainable future," *Marine Pollution Bulletin*, vol. 31, no. 4–12, pp. 159–166, 1995.
3. A.R. Brown et al., "Assessing risks and mitigating impacts of harmful algal blooms on mariculture and marine fisheries," *Review in Aquaculture*, vol. 12, no. 3, pp. 1663–1688, 2020.
4. M. Martinez-Porchas, L. R. Martinez-Cordova, "World Aquaculture: Environmental Impacts and Troubleshooting Alternatives", *The Scientific World Journal*, vol. 2012, Article ID 389623, 9 pages, 2012.
5. T. Wu, Y. Huang, J. Chen, "Development of an adaptive neural-based fuzzy inference system for feeding decision-making assessment in silver perch (*Bidyanus bidyanus*) culture," *Aquacultural Engineering*, vol. 66, pp. 41–51, 2015.
6. M. L. San Diego-McGlone, R. V. Azanza, C. L. Villanoy and G. S. Jacinto, "Eutrophic waters, algal bloom and fish kill in fish farming areas in Bolinao, Pangasinan, Philippines," *Marine Pollution Bulletin*, vol. 57, no. 6–12, pp. 295–301, 2008.
7. G. A. Santos, J. W. Scharma, R. E. P. Mamauag, J. H. W. M. Rombout and J. A. J. Verreth, "Chronic stress impairs performance, energy metabolism and welfare indicators in European seabass (*Dicentrarchus labrax*): The combined effects of fish crowding and water quality deterioration," *Aquaculture*, vol. 299, no. 1–4, pp. 73–80, 2010.
8. H. Sun, J. Li, L. Tang and Z. Yang, "Responses of crucian carp *Carassius auratus* to long-term exposure to nitrite and low dissolved oxygen levels," *Biochemical Systematics and Ecology*, vol. 44, no. 1, pp. 224–232, 2012.
9. M. Sun, S. G. Hassan, D. Li, "Models for estimating feed intake in aquaculture: A review," *Computers and Electronics in Agriculture*, vol. 127, pp. 425–438, 2016.
10. C. Zhou et al., "Near infrared computer vision and neuro-fuzzy model-based feeding decision system for fish in aquaculture," *Computers and Electronics in Agriculture*, vol. 146, pp. 114–124, 2018.
11. C. Zhou, et al., "Evaluation of fish feeding intensity in aquaculture using a convolutional neural network and machine vision," *Aquaculture*, vol. 507, pp. 457–465, 2019.