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Research Article

Digital Transformation of Feeding Control Knowledge in Marine Aquaculture using Current Sensors

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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 applying digital transformation (DX) on such knowledge by measuring underwater currents induced by fishes as indicator of their hunger. A prototype sensor suite consisting of current sensors, cameras, and an inertial measurement unit (IMU) was constructed to measure the currents around the fish cage, measure the motion of the suite, and record fish activity, particularly during feeding. An initial experiment was performed in two fish cages during feeding activity. Current measurements were collected and analyzed together with the recorded videos to relate the changes in current to the feeding activities. Results suggest that the currents increase around when feeding was started continuously and decline to zero around when it was stopped. However, more data needs to be collected and analyzed for a better understanding of the relationship between the changes in current and fish activities so it can be used to optimize the feeding decisions of fish farmers.

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 decision making in fish feeding. In many aquaculture operations, feeds make up a large portion of the production costs, accounting for as high as 86.7% [5]. Poorly timed and excessive feeding leads to poor cost-efficiency in raising fish [6]. It was estimated that 8.26% of the supplied feed gets lost to the environment [7]. Costs expended on the uneaten feeds would not be translated into further growth of the fishes and subsequently into the increase in their value, therefore reducing the potential income that could be made. In addition, these feeds would sink to the bottom of the sea to decompose, releasing ammonia and phosphate, nutrients that accelerate the growth of harmful algal blooms in the surrounding environment [8]. Decomposition of both feeds and algal blooms would consume dissolved oxygen, depleting the supply for the fishes as a result. Such threat would lead to slower growth rates, poorer quality of harvest, or at worst, massive fish kills [8,9,10]. Not only the profitability of the farm operation would be limited, but fish farmers could even lose their investment as a result [3,6,8].

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Japan, where marine aquaculture comprises majority of the country's aquaculture production, is not exempted from these issues. Production volume has remained stagnant throughout the years, without significant increases. With increasing prices of feed and imported fish meal among other factors, income on fishing in marine aquaculture households have decreased in 2018, as of the latest report [11].

The practice of feeding in Japanese fish farms involves the use of feeding machines mounted on boats. Efficient feeding has usually been achieved with decisions made by expert farmers, who would start and stop the feeding operation upon their sound assessment of the fishes' behavior. This would reduce the feed conversion rate, improving fish welfare and reducing costs [12]. In addition, 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 [13,14].

Digital transformation (DX), defined as the adoption of disruptive digital technologies to increase productivity, value creation and social welfare, has been embraced by an increasing number of industries, governments, and organizations around the world with the emergence of Industry 4.0 [15]. It has been seen as enabler of predictability, efficiency, and productivity by reducing operation costs and personnel, as well as increasing feeding efficiency [16,17]. DX of experts' knowledge in feeding would help them improve their feeding decisions, but also those of less experienced farmers. This would not only improve the amount and quality of their harvest and 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.

Especially with the recent advancements in artificial intelligence, intelligent feeding control has become one of main topics of current research efforts in aquaculture. Various methods have been developed to recognize and analyze fish feeding in water [12,18]. Applications vary from tracking fish movement to detecting feeds in water. Some of these methods feed the information collected into machine learning models to generate feeding decisions [6,14,19]. Different information technologies developed fall into three general categories: computer vision (CV), acoustic technologies, and sensors-based technologies.

Recognizing fish feeding with computer vision has been widely used in aquaculture in recent years, as optical sensors and machine vision systems are becoming more power and sensitive, while becoming less expensive throughout the years [20]. However, a significant issue in the application of computer vision is the complexity of the aquaculture environments causing various degradation to images [21]. While some methods use near infrared to adapt to low lighting and turbid water, their resolution and accuracy need to be improved.

Acoustic technologies overcome the problems of degradation brought by varying illumination and water turbidity conditions affecting the performance of computer vision, as sound propagates in water with minimal attenuation. However, each kind of method also encounter specific problems. The use of passive acoustics to detect feeding sounds are affected by ambient noise from aquaculture equipment and weather [22]. While tracking fish position and movement using with clarity and precision even in marine environments, equipment is relatively expensive [18,23].

Various sensor-based technologies are used for monitor fish feeding. With biotelemetry, fishes are accurately tracked with inertial measurement unit (IMU) or depth sensors, with data transmitted acoustically [24]. However, this method is invasive, which may affect the welfare of the fish. Implanting trackers would also be difficult to do for thousands of fishes in a cage. The same problems apply to using electromyogram (EMG) transmitters, which classifies fish hunger states with high success [25]. On the other hand, measuring water quality using sensors for parameters such as dissolved oxygen and temperature are non-invasive [6,26]. Generating feeding decisions using these sensors had high success rates, as these measurements are related to fish hunger. However, these are also susceptible to other water quality parameters [18].

A measurement that has been barely explored for making fish feeding decisions is of underwater currents generated by fish movements. It has been studied that circular swimming patterns of fish schools such as salmon push water out of cages, inducing outward flow [27,28,29]. It is also known that farmed fishes tend to swim close to the surface when hungry, and swim at the deeper parts of the cage when satiated, as shown in Fig. 1. By knowing the currents at different depths, we could gain better understanding of the behavior of fishes in a

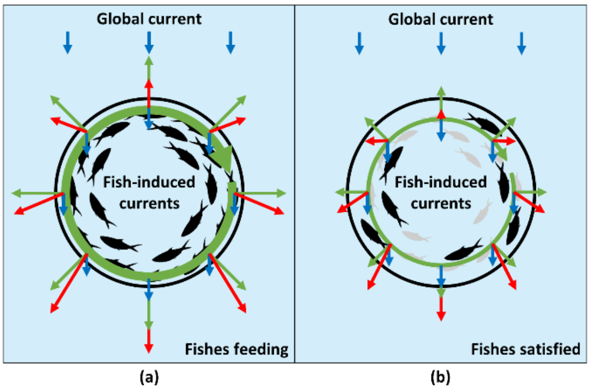


Fig. 1. Top-view concept of changes in underwater currents in relation to fish feeding behavior. More water flows out of the cage when more fish are feeding at surface (a) and less water flows when fishes go back to the deeper part of the cage (b).

feeding activity – the depths and speeds at which they are swimming, and of the decision-making process of an expert fish farmer. In turn these insights could be useful for optimizing the feeding control which could also help less-skilled farmers improve their feeding decisions.

So far, a group of researchers have proposed a sensor system for monitoring various measurements in water, including fish displacement speeds using sensors sensing fish-generated flow at multiple depths [30]. These speed sensors were calibrated by current sensors placed outside the cage. All sensor data were then fused into feeding control decisions. Using gathered real-world measurements, they made simulations of feeding activities in cages using their system and minimized uneaten feeds in water.

Our research revisits the approach of measuring underwater currents for fish feeding control in marine aquaculture farms. By measuring the currents around the fish cage at different depths during feeding activities, we can estimate their feeding behavior reliably at varying environment conditions. We can analyze the relationship of the changes in these measurements with the events in feeding activities, at which the expert farmers would change the amount of feeding. We can then determine the measurement changes that would optimize the feeding regimen, thus applying DX on the expert farmers' knowledge in fish feeding. This paper discusses about the envisioned design of the sensor system, the development of the prototype sensor suite and the initial current measurement experiment in a fish farm using the said prototype.

2. Sensor System Architecture

In the envisioned system, a network of sensor nodes is placed around fish cages with diameters of up to 40 meters and depths of up to 20 meters, as shown in Fig. 2. Each node consists of multiple current sensors measuring current velocities for every depth of choice. In addition to measuring currents, it also has water quality sensors (dissolved oxygen, temperature, conductivity, pH, etc.) at multiple depths. It has at least one underwater camera 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 before timestamping them.

In each cage, sensor nodes communicate in a star Wi-Fi network, where one node is designated as the master and the rest as slaves. Slaves send their measurement data to the master, which may or may not have its own sensors for collecting measurements. Data sent to the master are transmitted either directly to the onsite farmer's device, which is connected to the master, or to a super master, which sends these data to a cloud server via 3G, 4G or 5G.

In addition to collecting sensor data, the farmer's devices can also send and access various data – fish information, feeding history, etc. – to and from the cloud server. In another cage, an automatic feeding machine is connected to the master which operates at the command

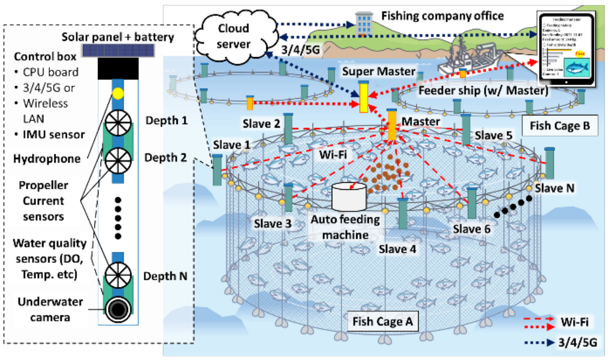


Fig. 2. Design of a sensor system in a fish farm with multiple sensor nodes, consisting of various sensors, deployed in multiple fish cages, collecting data for the farmer on ship as well as for the fishing company during feeding activities.

from the cloud server, which calculates the timing and amount of feeding from the collected data. This machine can also send its status to the server so the farmer can perform maintenance on it. Finally, the fishing company office has access all to data from the farm through its connection to the cloud server.

3. Sensor Suite for Initial Measurements

3.1. *Sensor suite system design*

For the initial measurements, two custom-built current speed loggers were mounted on a metal frame at two different depths at which fishes were observed before, during, and after feeding. These sensors measure only one flow axis given their fixed mounting. An inertial measurement unit (IMU) logger was mounted closest to the current sensor of interest. This would measure movement of the frame caused by fish-induced currents. These sensors were remotely triggered by Bluetooth to start logging measurements before they were placed underwater for hours. Alongside the current sensors were underwater cameras for visual recording of fish activity, which were switched to operate before getting submerged underwater. These observations were used to analyze their activity at points of interest with significant changes in current measurements. Fig. 3a shows the setup of the initial experiment.

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 would be cancelled from the outgoing current. Due to time constraints, however, one set was constructed and 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 would be performed, we decided to develop our own current sensors for lower development costs. The sensor developed for this experiment was a modified propeller-type flow sensor originally intended for measuring water flow through water pipes, as shown in Fig. 3b. Its Hall-effect sensor generates pulses proportional to the magnetic propeller's rotation.

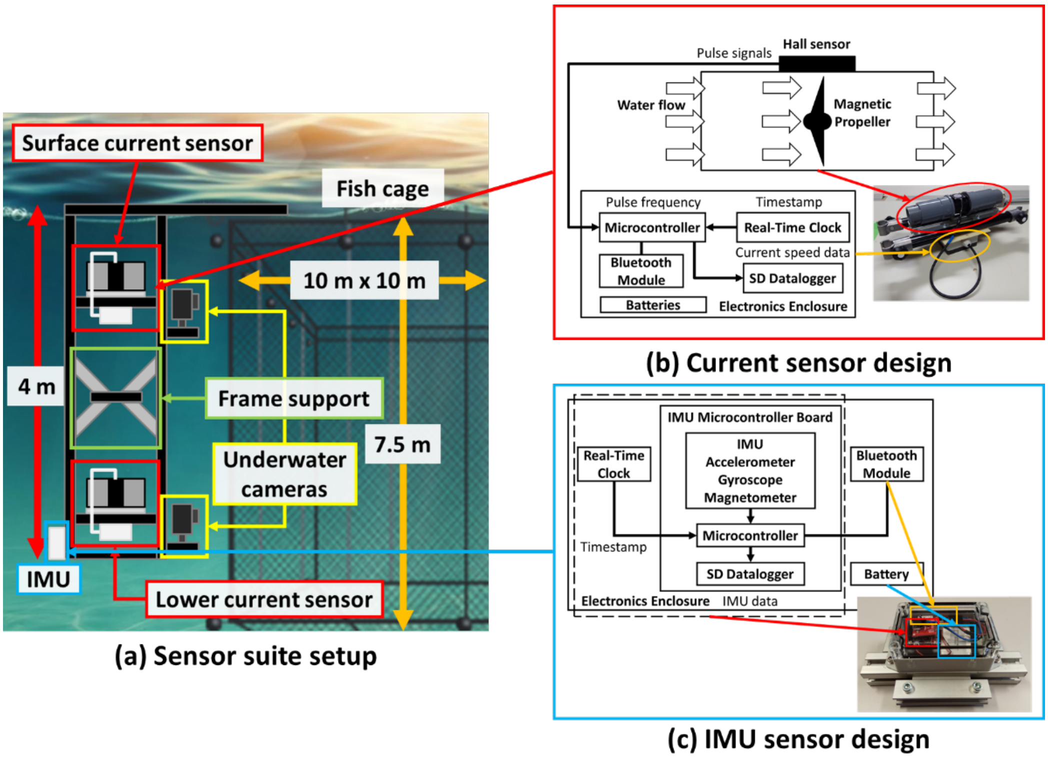


Fig. 3. Design of the initial farm experiment using the prototype sensor suite consisting of current, camera, and IMU sensors (a). The current sensors (b) and the IMU sensor (c) were designed to perform and log measurements underwater during a feeding activity.

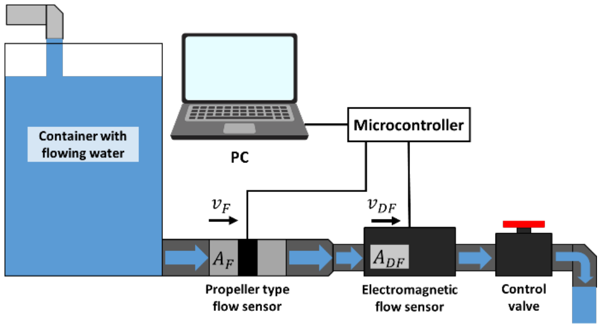


Fig. 4. Calibration test setup of the current sensor where it is connected to a digital flow sensor as they both measure water flow from the container

An Arduino microcontroller would count these pulses for a given period, obtain the average frequency throughout the period, and then calculate the current speed using a calibration coefficient. It would then add timestamping to the reading and store it in a microSD card with its datalogging shield with SD and RTC capability. A Bluetooth module was also connected so it could be triggered remotely by a computer to start and stop measurements.

Each current sensor was 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 were housed in an IP68 enclosure.

The mounting for the sensors was a 4-meter aluminum structure with four legs to which the sensors were attached to. The sensors depth was adjustable by sliding them through the legs. For the initial and the succeeding experiments, it was decided to position the two sensors three meters apart. In the prototype, they were fixed at 0.7 m and 3.7 m from the top of the frame, respectively. Each leg was made of three four-meter frames. A cross-like reinforcement was attached at the center of the frame to minimize 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, as shown in Fig. 4.

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

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

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 were classified as the discrete readings from the custom sensor. Readings using the 10-second configuration were more continuous. However, there were higher chances of averaging high and low sample values, which may not properly represent the actual measurement. Using the 5-second period seemed to be a favorable configuration as there were perceived smaller chances of samples with large differences, while its readings were still continuous. This was therefore the selected configuration for the upcoming experiments.

3.3. *Underwater IMU sensor and cameras*

The IMU sensor was a Sparkfun 9DoF Razor IMU M0, a very compact microcontroller with an MPU-9250 IMU and a µSD 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 was able to timestamp its measurements before writing them to a 32 GB µSD card. Powered by a 1000-mAh lithium-ion polymer (Li-Po) battery, it was enclosed in an IP68 enclosure, as shown in Fig. 3c. Power endurance test result showed that this sensor could collect data for around 22 hours as well.

Two GoPro cameras were mounted on the frame alongside the current sensors. Each had a 512 GB µSD card to be able to record as much fish activity as possible. Fully charged, each camera can capture videos for around 80 minutes, around the same amount of time feeding is made.

4. Initial fish farm current measurements

4.1. *Experiment overview*

On March 18, 2021, we performed the initial current measurement experiment at a fish farm located in Usuki City in Oita Prefecture. Measurements were made at two 100 m^2 square cages with depth of 7.5 meters while feeding operations were done by the farmer. These cages contained around 3500 yellowtail amberjack (*Seriola lalandi*) fishes, locally known as *Hiramasa*. The fishes had been raised for a year and each weighed around 3 kilograms. Each feeding operation lasted around 80 minutes.

The sensors were powered on, closed, and triggered to record data before submerging them for measurement. As shown in Fig. 3a, the sensor frame was then mounted on one side of the fish cages. The cage frame on which the sensor frame was mounted on was elevated at 0.3 m above water. The sensors were therefore positioned at depths of 0.4 m and 3.4 m, respectively. This experiment provided insight for validating or improving the design of the proposed sensor system.

4.2. *Results and Discussion*

Due to human error, the IMU was left open before submerging in a trial measurement before the measurement of the target cages, permanently damaging it without having collected any data. As for the video recordings, due to insufficient battery power from trial recording, only the first half of the feeding at the first cage had underwater recordings. For the second cage, video recording above surface was taken instead.

The measurement data was post-processed by calculating the moving average of the readings from the last 30 seconds of measurements. This is to smoothen the plot for easier understanding of the measurements. From this point throughout the discussion, the tern "measurements" and "readings" refer to the moving averages. Noted observations were marked on the plot according to the time they were recorded. The changes in measurements were also analyzed with the video recordings of fish activity at the time of the noted observations. It was noted in both measurements that the spikes before and after a series of zero readings indicate the time the sensors were deployed and recovered.

In the first fish cage, feed was started to be given in small amounts at around 11:34, seven minutes after the deployment of sensor, to attract the fishes to the surface, and was dispensed continuously at around 11:43, nine minutes later, as shown in Fig. 5a. Before feeding began, video recordings showed no presence of fish at the surface, as shown in Fig. 6a. They were seen shoaling below, as seen from the second camera. At the start of feeding, measured current at the surface did not increase right away. Fishes started schooling and few started swimming to the surface only at around 11:36, as shown in Fig. 6b. The number of fish swimming to the surface continued increasing before the feeds started floating away from the cage, blurring the surface camera at around 11:42. Despite this observation, current readings did not indicate significant increase in current.

Significant increase in surface current started at 11:43. At around this time, the fisherman also started dispensing feed to the cage continuously. It was also around this time that the fishes at 3.4 meters depth became significantly less visible. This could be attributed to the decrease in illumination due to the increased fish activity at the surface blocking more light, as well as to dispersion of light from splashing. At around 11:47, vigorous fish feeding was observed from the surface. This was also observed from the surface underwater camera, as shown in Fig. 6c, although with difficulty due to blurred water. This could be partially attributed to the single lens property of the cameras, therefore lacking the ability to adjust its focus to infinity. Movement from fishes at surface appear to be slightly faster than fishes at 3 meters below. From this point towards the end of the video, the visibility of fishes would back-and-forth increase and decrease. Due to insufficient battery power, the underwater cameras stopped recording at 12:09 (surface)

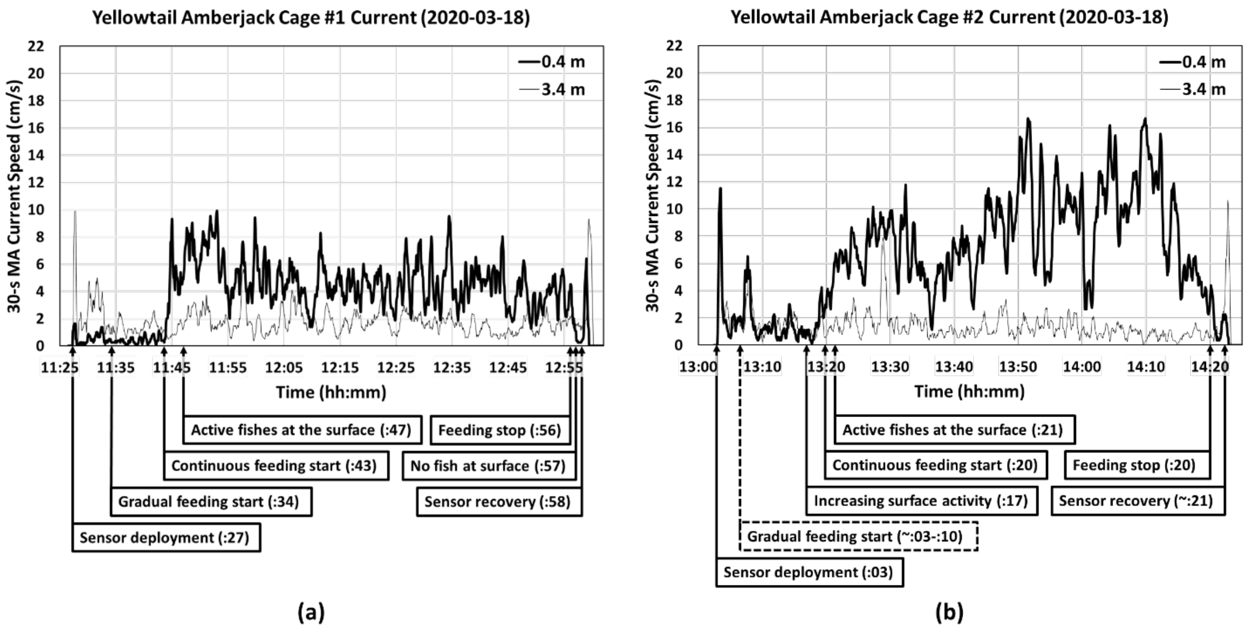


Fig. 5. 30-second moving average of current measurements at the first fish cage (a) and at the second cage (b). Feeding activity in both cages lasted for around 80 minutes, not including sensor deployment.

and 12:04 (3.4 m depth), about halfway of the feeding activity.

Throughout the feeding, measurements at the surface were generally higher than those at 3.4 meters. The trend in measurements throughout the activity was generally uniform, with peak values ranging within 4-10 cm/s. Low feeding activity on that day was noted by the farmer. Current reading was at 4.51 cm/s when the fisherman stopped dispensing feeds at 12:56. It was noted that fishes were still swimming around the surface at that time. One minute later, measurements dropped to almost 0 cm/s, the same time it was noted that fishes were no longer visible from the surface, indicating that they swam back to the deeper part of the fish cage.

In the second cage, the time gradual feeding started was not noted properly, as it conflicted with the time of sensor deployment. It could have begun sometime after 13:03, when the sensors were deployed, as indicated by the sensor readings, as shown in Fig. 5b. At the start of the video at around 13:10 (Fig. 7a), few fishes were swimming up during gradual feeding. Measurements remained low, up to 2.51 cm/s. At 13:17, while there was no increase in current yet, feeds started to disperse from the cage, as observed in the video. As shown in Fig. 7b, more fishes started swimming at the surface at 13:19, with even more splashing observed, and readings reaching over 4 cm/s. The fisherman switched the feeding machine to dispense continuously at 13:20. The fishes were observed to be actively swimming at the surface one minute later, with current readings exceeding 6 cm/s.

The measurements at 3.4 m depth in the second cage were also generally lower than those at 0.4 m depth. But unlike in the first cage, there was an increasing trend in the surface measurements at the second cage from, with a few drops throughout the continuous feeding. Current measurements peaked at 13:51, at 14:04, and at 14:09, exceeding 16 cm/s. Feeding was ended at 14:20, at which measurement was at around 4 cm/s. Reading eventually dropped to almost zero after around one minute, just a few moments away from sensor recovery. At around this time, surface of the cage became calm, as shown in Fig. 7c.

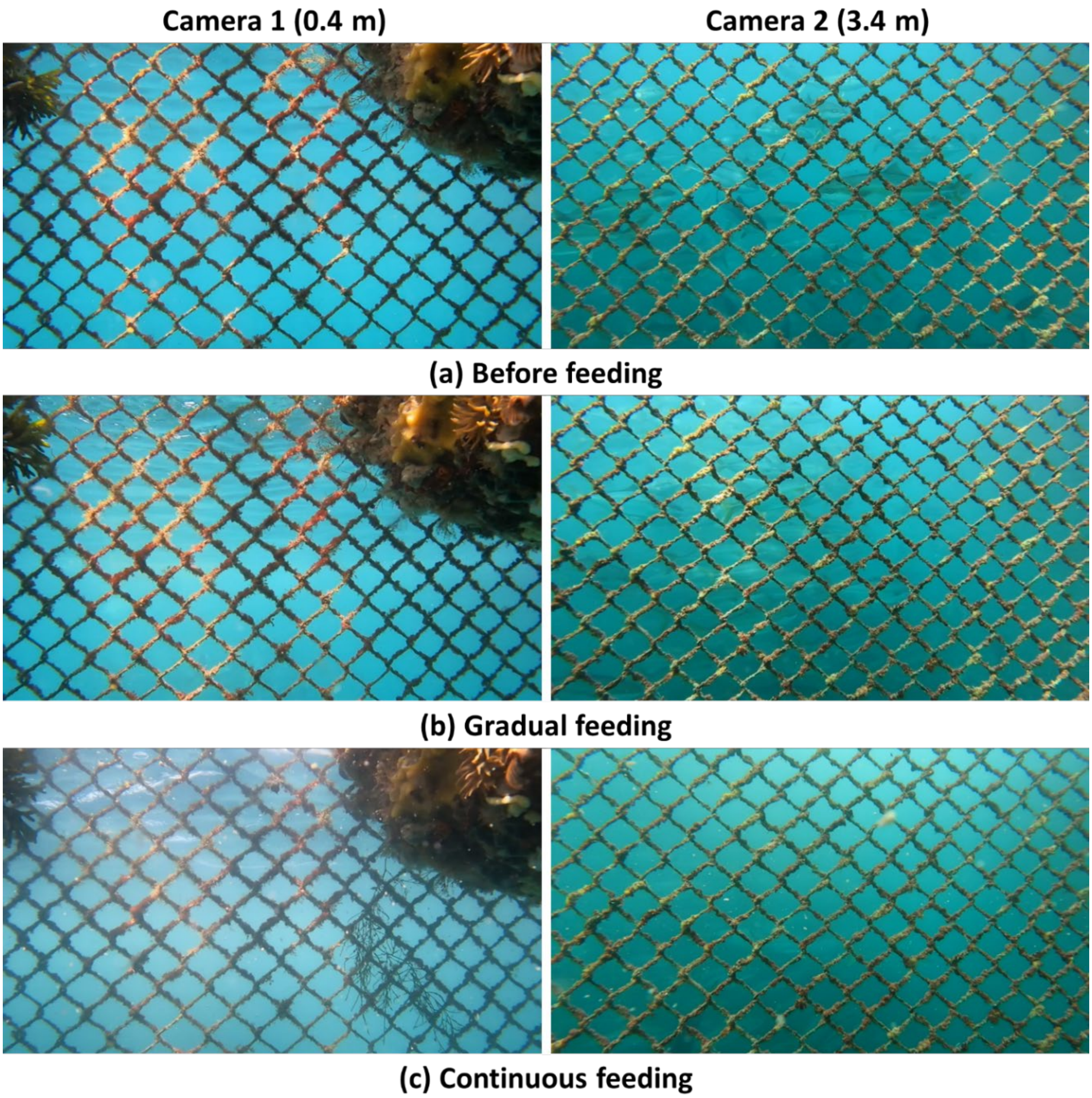
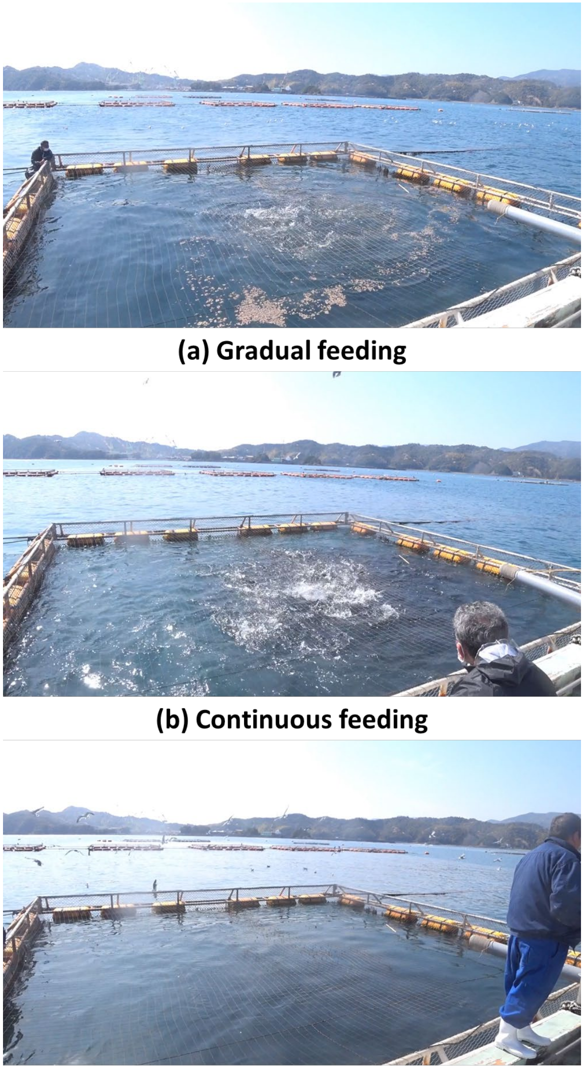


Fig. 6. Snapshots of video recordings at the first fish cage at the start of measurement (a), at the start of gradual feeding (b), and at continuous feeding (c). Feeding activity in both cages lasted for around 80 minutes, not including sensor deployment.

A similar observation for both feeding activities was that current measurements were at around 4 cm/s when feeding was stopped by the fisherman. Both gradually dropped to almost zero after around one minute. As for switching from gradual to continuous feeding, it is still difficult to determine the threshold since currents when continuous feeding started at different cages were different. However, it can be observed that increases were gradual and consistent, eventually exceeding 6 cm/s.



(a) Gradual feeding

(b) Continuous feeding

(c) Feeding stopped

Fig. 7. Snapshots of surface recording at the second fish cage during gradual feeding (a), during continuous feeding (b), and after feeding was stopped (c).

Based on the data, changes in current, especially at the surface, correspond to changes in fish behavior as observed by the farmer, although more data needs to be collected and to be studied further.

5. Conclusion and future work

This paper presented the 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 kinds of sensors could record measurements reliably for at least 22 hours.

The sensors were deployed in the two fish cages for measurements during a feeding operation. Especially at the surface, changes in current outside the cages were observed to correspond to changes in fish behavior and appetite as observed by the farmer, prompting to start and stop feeding. However, more data needs to be collected to verify this observation.

Future work also includes development of a network of sensor nodes as described in the system architecture using more robust current sensors. These are future research tasks towards implementing DX in fish feeding in marine aquaculture farms.

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Authors Introduction

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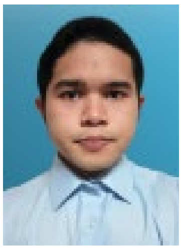

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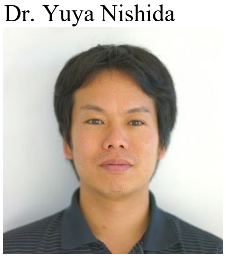

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