Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 55-31 (2022) 401–408

Autonomous Monitoring and Inspection Operations with UUVs in Fish Farms ⋆

E. Kelasidi * B. Su * W. Caharija * M. Føre ** M.O. Pedersen * K. Frank *

* SINTEF Ocean, Dept. of Aquaculture Technology, Norway
** Norwegian University of Science and Technology, Norway

Abstract: In this study, a general control framework for autonomous operations in highly complex and dynamically changing environments such as fish farms is proposed and experimentally validated. Since fish farms feature an environment that includes fish, deformable flexible structures and highly variable environmental disturbances, the framework is designed to interact with these. The proposed control approach integrates estimates of the cage structure dynamics and fish behavior, adaptive path planning and path following control concepts in one unified and compact framework that could be used to implement and demonstrate different concept studies in dynamically changing environments. The performance of the control framework is investigated though field trials using a remotely operated vehicle (ROV) in a commercial fish farm. Experimental results show that the proposed framework can be applied to challenging operations in fish farms.

Keywords: Precision fish farming (PFF), path planning, path following, autonomous aquaculture operations, unmanned underwater vehicles (UUVs).

1. INTRODUCTION

Fish farming is an important global provider of seafood aiming to contribute to meeting the growing global gap in supply and demand of food for human consumption (FAO, 2020). The fish farming industry faces several challenges to reach the current demands, where several day-to-day operations conducted in fish farms are still manually performed and rely on personnel experience. In consequence, the HSE risks in this sector are high, resulting in relatively high frequencies in work-related injuries. This indicates that the benefits of increasing the automation level of high-risk operations in aquaculture include social and ethical, as well as economical aspects (Bjelland et al., 2015). Increased use of automation will also improve the human control in such operations. Success stories from other marine industries imply that unmanned underwater vehicles (UUVs) may be useful tools for solving this challenge, an idea that was first introduced by Balchen (1991). Using UUVs may lead to improved precision and efficiency in operations, which in turn will make operations more sustainable. This is also in line with the Precision Fish Farming (PFF) concept, which is an emerging concept that outlines how operations in fish farming may be industrialised, digitised and improved through the sensible adaptation of innovative technologies and automation principles (Føre et al., 2018).

Scientific literature related to UUVs covers aspects of modelling, sensing and control for different platforms ranging from Remotely Operated Vehicles (ROVs) and Autonomous Underwater Vehicles (AUVs) (Antonelli, 2014; Caharija et al., 2016; Fossen, 2011), to the more recent multi-articulated slender body underwater robots (Kelasidi et al., 2016, 2017). Most of these studies consider simplified dynamic models of UUVs, their interaction with environmental effects and navigation in static environments, and are thus limited to addressing vehicles subjected to highly idealized conditions (Antonelli, 2014; Fossen, 2011; Kelasidi et al., 2016). Studies using such simplified approaches have increased our fundamental understanding of UUV dynamics and control approaches for these. However, since practical applications of UUVs generally include motion in complex environments, it is essential that methods for UUVs are verified and validated before industrial deployment.

Although the risks and implications of introducing UUVs to more extreme marine environments such as fish farms have been analysed in generic terms by Bjelland et al. (2015) and Balchen (1991), UUV-operations in dynamically changing environments have not been extensively studied in literature. This also applies to UUV operations related to flexible/deformable structures. While most published research on control strategies for UUVs focus on rigid structures and constant environmental conditions (Antonelli, 2014; Bjelland et al., 2015; Fossen, 2011; Føre et al., 2018; Kelasidi et al., 2016; Ridao et al., 2014), vehicle navigation in fish farms will require new control concepts that relate to fish and flexible structures and compensate for environmental variations. This comprises a challenging environment for autonomous operations, and to cope with this, a UUV needs to sense and/or estimate the local navigation environment, and adapt the control system mechanisms and responses to this. Furthermore, autonomous operations with UUVs in aquaculture are still limited since the control methods required for enabling vehicle interaction with a dynamic biomass and flexible structures (e.g., nets, ropes) are non-existent.

While there are published studies aimed at underwater robotic system navigation in the presence of animals and deformable structures (Amundsen et al., 2022; Bjerkeng et al., 2021; Chalkiadakis et al., 2017; Karlsen et al., 2021; Livanos et al., 2018; Su et al., 2021; Wu et al., 2021), the control strategies for this purpose are not as well established in science as conventional approaches. Amundsen et al. (2022) developed and tested a net-relative path following method based on measurements from a

⋆ This work was funded by the Research Council of Norway through the projects (CageReporter, 269087) and (CHANGE, NO313737).
Corresponding author: eleni.kelasidi@sintef.no

10.1016/j.ifacol.2022.10.461

Doppler velocity log (DVL) in a commercial fish farm. However, since the accuracy and measurement noise level of a DVL tends to increase when fish are present between the beam and the vehicle, the proposed method would face challenges when applied during fish farming operations. Another interesting study was done by Rundtop and Frank (2016) who tested a semi-autonomous net following concept based on measurements from a DVL and an Ultra Short Baseline (USBL) for ROV navigation in fish cages. However, since the structural dynamics of the sea-cage was not considered in that study, and the accuracy of the underwater position system was between 1-2 m, this method would too experience shortcomings in an operational setting. These observations imply the need for a more targeted development of new control strategies for operations in fish farms.

Developing new control strategies for UUV-operation in new environment types is typically done by adapting control concepts developed for applications in other industries and demonstrating the concept by performing some tasks autonomously or semi-autonomously. However, this approach is unsuitable for adaptation to operations in fish farms as living animals and flexible structures are complicating factors rarely encountered in other situations, and since a UUV in a fish farm will be physically constrained by the net cage. Control strategies for UUVs in fish farms will therefore need to include information on fish behaviour, structural deformation and the environment in the feedback control loop to achieve adaptive locomotion. This will include methods for fish-machine interaction, enabling the robot to accomplish inspection and intervention tasks while interacting with the fish, and methods for responding to deformable structures and changing environments. Preliminary studies have been carried out on behavioural responses of fish in the presence of robotic operations (Kruusmaa et al., 2020), but none of these have solved the challenges associated with fish machine interactive autonomous control. The knowledge from such studies needs to be combined with existing knowledge on UUV control systems to develop interactive control functions for autonomous navigation of UUVs.

Intelligent and interactive path planning will be a key-component in developing the future control strategies for fish farms. Specifically, such approaches will be needed to plan paths that allow the vehicle to inspect areas considered interesting, while avoiding colliding with the infrastructure of the fish cage and disturbing (e.g., 'scaring') the fish during the operation. Potential measures to achieve this may include keeping the vehicle at a constant distance from the fish, or by slowing down when the fish exhibit flight responses. Unlike for conventional approaches, where the path is planned off-line using *a priori* knowledge, path planners for UUVs operating in fish farms will need to interact with large numbers of fish and flexible and highly deformable structures that are susceptible to environmental disturbances. This means that one will need more detailed data on both vehicle position and orientation, and environmental data. Such data can be obtained using different localization and control techniques based on complex sensors and real-time processing onboard the vehicle.

Any new control strategies, algorithms and estimators to be used for vehicle control need to be sufficiently verified before becoming eligible for industrial exploitation. This should preferably be done in a relevant environment to explore the system's ability to cope with expected and unexpected conditions during intended applications. While controlled laboratory trials can be used to verify individual system components and details, relevant application scenarios should be studied in field trials. In the case of in-cage navigation this entails conducting experiments in real operational fish farms with flexible cages containing a biomass at commercial density that are exposed to variable environmental conditions. Moreover, the experiments should also use vehicles that could be relevant tools for fish farming operations, such as ROVs.

This study presents a new general control framework that can guide and maneuver a UUV during inspection and possibly intervention tasks inside fish cage structures while avoiding collision with the net, other infrastructure components and the biomass. The feasibility of the proposed control framework was demonstrated in field trials in a fish farm using a Remotely Operated Vehicle (ROV) Argus Mini ROV. Experimental results were analysed to evaluate if the proposed general control framework can be used to achieve daily underwater structure monitoring and inspection tasks in fish cages using UUVs. To the best of the authors' knowledge, general control frameworks for UUVs operating in fish farms have not been extensively investigated in existing literature.

The paper is organized as follows: The general control framework is presented in Section 2, followed by the presentation and discussion of the experimental results in Section 3. Conclusions and discussions for possible futute expansions of the proposed approach are given in Section 4.

2. CONTROL FRAMEWORK

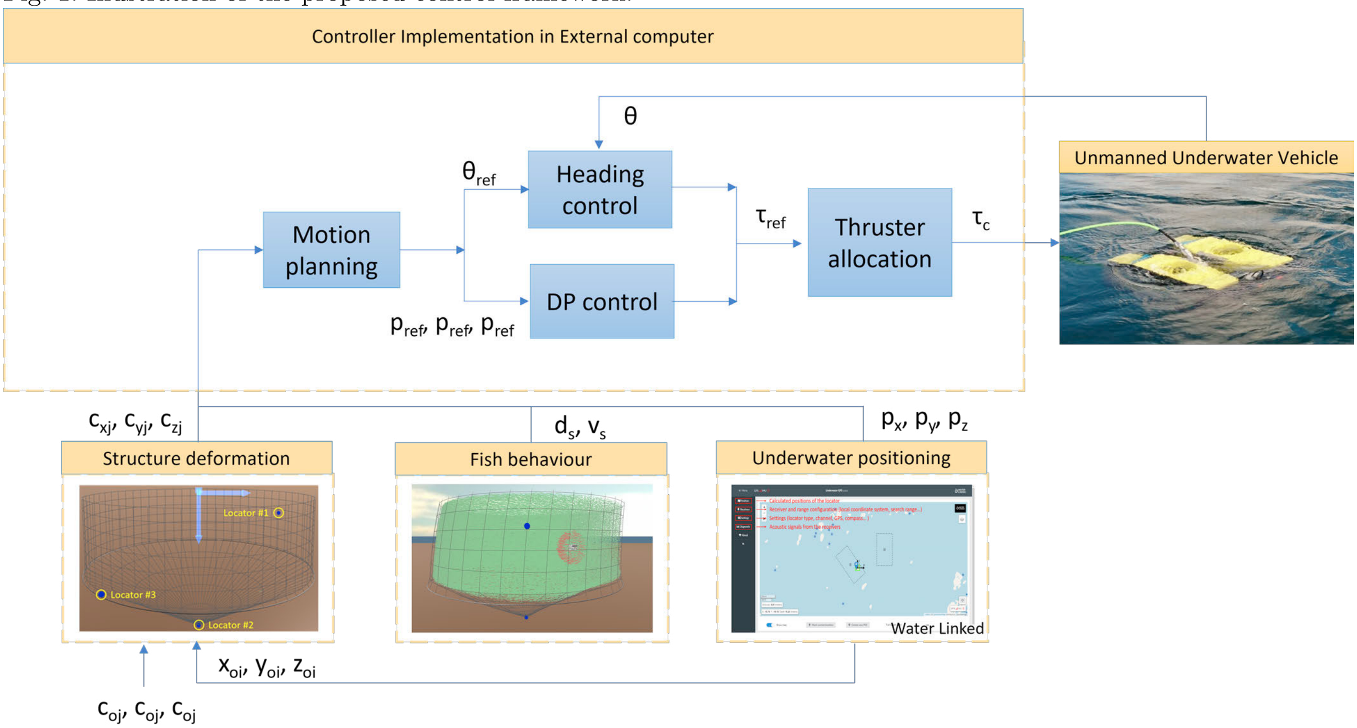
This section presents a novel control strategy for UUVs operating in dynamically changing environments. The strategy has been designed to be able to adapt the motion and actions of vehicles to limit how much they disturb the cultured fish. This will enable the robot to adapt its motion to the dynamic environment during autonomous operations, thus avoiding collisions or undesirable impacts on fish behaviour (e.g. scaring the fish). Fig. 1 shows the illustration of the proposed general control framework.

2.1 Implementation platform and existing foundation

All the different components of the proposed general control framework have been integrated in FhSim (Reite et al., 2014; Su et al., 2019) since this simulation platform can be used both for extensive simulations studies and for actual demonstrations with different UUVs. FhSim features numerical models of fish behaviour (Føre et al., 2009, 2014), flexible aquaculture and fisheries systems (Endresen et al., 2013; Enerhaug et al., 2012; Moe-Føre et al., 2014) and the sea environment (i.e., waves and current Reite et al. (2014)). FhSim also features real-time interfaces with sensors (e.g., DLV, USBL, underwater cameras, laser and the WaterLinked underwater positioning system) and actuators, enabling the porting of control systems developed and tested in the simulation environment directly to physical experiments using real vehicles. Measurements from the field trials have been used to verify the implemented methods. This is done through communication via TCP/IP- and UDP-links that can also interface FhSim with other applications, as well as serial interfaces for vehicles such as Argus Mini ROVs and BlueROV2.

FhSim features 4DOF and 6DOF models (Fossen, 2011) of UUVs that have been validated for Argus Mini ROVs (Amundsen et al., 2022), BlueROV2s and the net-crawling robot Remora (Føre et al., 2021). In addition, several estimation methods such as 4DOF extended Kalman filter, unscented Kalman filter and nonlinear observers have been implemented in FhSim to estimate the structural deformations (Su et al., 2021, 2019). The framework also features different motion planning and guidance methods including Waypoint guidance (Fossen, 2011), 2D and 3D

Fig. 1. Illustration of the proposed control framework.



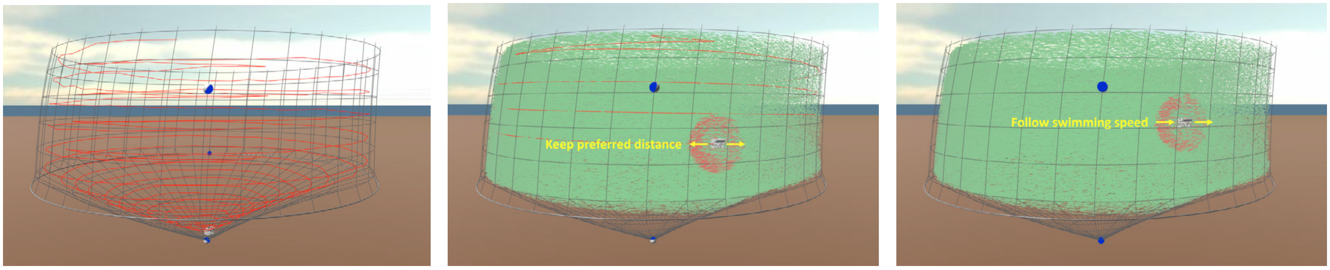
ILOS guidance (Caharija et al., 2016), net-relative guidance (Amundsen et al., 2022) and the elastic band method (Føre et al., 2021). Finally, FhSim contains various controllers such as PID, sliding mode, adaptive backstepping that can be used to control depth, heading, speed and dynamic positioning (DP), and that have been tested in the field.

2.2 Control system components

In this study, all the mentioned components of FhSim have been integrated with the structural deformation concept used by Su et al. (2021) and the fish behaviour model presented in (Su et al., 2019) in a common general control framework for experimental demonstration of autonomous navigation of UUVs in fish farms. The proposed control framework features three components: a) an estimator of the cage structure dynamics and the cage environment, b) an estimator of fish behavior, b) modules for path planning and path following control.

Estimation of cage structure dynamics and cage environment: The conditions at sea-based fish farms include several features that are determined by the ambient environment (e.g., temperatures, oxygen, light, water currents and sea states/waves), and thus are outside human control. Some of these environmental features are known to influence fish behaviour (Oppedal et al., 2011) and some of them (i.e., waves and currents) may also cause structural deformations in flexible cage components (Lader et al., 2008). In sum, this yields a very complex situation for navigation and autonomous operation of UUVs, and it is therefore important to estimate these features when aspiring to realize the operation of UUVs in a fish farming situation. To achieve this, fish cage deformation has been addressed by developing observers that use established estimator methods such as Kalman filtering (Su et al., 2019) or non-linear observers (Fossen, 2011) to combine *a priori* knowledge of the cage structure shape with real-time data from position measurements attached in different points of the cage. To ensure sufficiently high data density for real-time control purposes, the structural deformation is estimated at each simulation/sampling time step when conducting operations in fish farms. This integration between the structural models and locator data can also be used to estimate the water current profile (Su et al., 2021).

Estimation of fish behaviour: The fish also comprise a key feature in the environment facing a UUV operating in a sea-cage, and it is hence necessary to address when developing control systems for this application. Specifically, it is essential to both describe where the fish are and how they behave, and how they respond to the presence of a UUV. There has only been one study where the impact of UUVs on salmonid fish in sea cages has been studied. In Kruusmaa et al. (2020), Atlantic salmon showed a stronger behavioural response to a thruster-driven UUV compared to a bioinspired robotic system, indicating that the design, movement and propulsion system of UUVs can affect fish behaviour. While the preliminary observations from that study are not sufficient as inputs for realistic model development, they clearly indicate that the fish responses should be used as inputs in the control of the robotic systems to minimise unwanted interaction between UUVs and fish. In this study, the fish behavior model implemented in FhSim has been integrated into the control framework to simulate and demonstrate autonomous functions that can account for and react to the responses of the fish. The individual-based fish behaviour model (Føre et al., 2009) can simulate full-scale commercial fish populations (i.e., 200,000 individuals) that respond to temperature, light, feed and cage deformations. For the estimation of fish-machine interaction, the fish are assumed to want to keep a certain distance (e.g., 2-5 meters) from the UUV. This distance was found based on qualitative observations made previously by echo-sounder and/or camera data, but could be set up to be adjusted based on real-time data. It is also possible to make the UUV follow the average fish swimming speed based on outputs from the fish behaviour



(a) Constant distance from net (b) Keeping constant distance from fish (c) Considering swimming speed of fish

Fig. 2. Simulated case studies for autonomous navigation of UUV.

model or real-time inputs from echo-sounders and/or cameras.

Path planning and path following control: The third component of the control framework comprises the modules responsible for path planning and path following. For this framework, this was realised by applying the so-called three-layered concept which consists of global path planning, local path re-planning, and path following control. The main aim of this approach was to exploit the knowledge of the structural deformation and the fish behavior provided by the estimators to enable interactive path planning and path following within sea-cages. The global path was acquired through off-line planning using *a priori* knowledge on the fish cage structure and fish behaviour (e.g., initial cage deformation, relative distance from the robot and fish swimming speeds). Local adaptations of the generated path (e.g., path deformation to overcome unexpected obstacles) is then performed for each time step using constraint functions. These functions are designed to prevent collisions with the net and getting too close to the fish, and thus use inputs from the online estimations of the net structure (e.g., closest net panel, distance to the net) and the fish behaviour (e.g., relative distance to the fish, fish swimming speed). The third step entails feeding the estimated path to the control system to function as a reference point for the path following system. Several simulated case studies have been tested to demonstrate the efficacy of the proposed control framework (Fig. 2).

3. EXPERIMENTAL INVESTIGATION

This section is focused on testing the complete system including real-time estimation of cage deformation, the Argus Mini ROV and the novel control framework proposed in this paper. Fig. 3 shows the illustration of the adapted experimental setup. The navigation performance of the control framework presented in Section 2 was investigated experimentally by tests following a) a straight line, b) a square path and c) curved paths.

3.1 Experimental setup

The experiments were conducted at a commercial farming site (SINTEF ACE/Salmar ASA ,Rataren in Frøya in Norway) that features 15 cages (50 m in diameter, 30m/45m deep), one environmental buoy and one welfare meter logging environmental conditions at the site. Cages at the site are moored in a grid system, with each cage featuring a cylindrical net structure, a floating collar, a sinker tube and ropes, all of which are flexible structures that deform with environmental forces. The trials were conducted in a cage equipped with cameras on a winch and contained approximately 200.000 fish during the experiments.

The experiments were carried out using an Argus Mini ROV (90kg weight, L: 0.9 m, W: 0.65 m and H: 0.6 m) that can operate down to 600 m depth and have up to 15kg payload. The Argus Mini ROV carried state-of-the-art sensors for navigation and positioning (IMU, depth sensor, localisation sensors), for monitoring fish (cameras with computer vision) and for monitoring the environment (net proximity and environmental conditions through HOBO Pendant and miniDOT loggers). The cage was equipped with a low-cost, hydroacoustic subsea communication system from WaterLinked AS which has been developed and adapted for use in fish cages. This system has previously been found to provide accurate real time measurements of the position of an ROV (max positioning error of ± 0.5m) and positions on the net structure for online estimation of cage deformation (Su et al., 2021).

For the real-time structural deformations, the WaterLinked underwater positioning system was deployed with three locators (WL-21009 Locator-A1) placed on a sea-cage to measure the horizontal positions of the net. These were set at 6.3 m (bottom edge of the lice skirt), 16 m (at the sinker tube) and 32 m (at the bottom weight) depths. Four receivers/transducers (WL-21005 Receiver-D1), three mounted at one side of the cage, hanging down from the floating collar, were used to pick up the acoustic signals from the locators. The fourth receiver was suspended at the opposite side of the cage to increase transducer spacing, and hence improve positioning accuracy. Resulting locator positions were given as coordinates relative to the placement of the baseline transducers, and were converted to a cage-referenced coordinate system fixed to the floating collar before further use. Cables were used to connect the locators and receivers to a topside cabinet designed to relay the obtained signals to an external computer via an integrated 4G modem. However, during these trials, a PC was connected directly to the topside cabinet through a local network to directly import the real-time positioning data to a numerical estimation model with minimal latency. The positions of the three locators were combined with numerical models to estimate the structural deformation as described earlier (Su et al., 2021), and the estimated positions of net structure was fed back to the motion planning algorithm to achieve interactive motion control of the underwater vehicle.

The ROV was positioned by attaching a separate locator (WL-21018 Locator-U1) to the vehicle, and using four dedicated receivers (WL-21005 Receiver-D1) (Fig. 4). These receivers were configured and adjusted such that it was possible to convert measured ROV positions into coordinates within the same local coordinate system as that used to position the net (Fig. 4). Experimental results from the controlled lab and field trials presented by Su et al. (2021)

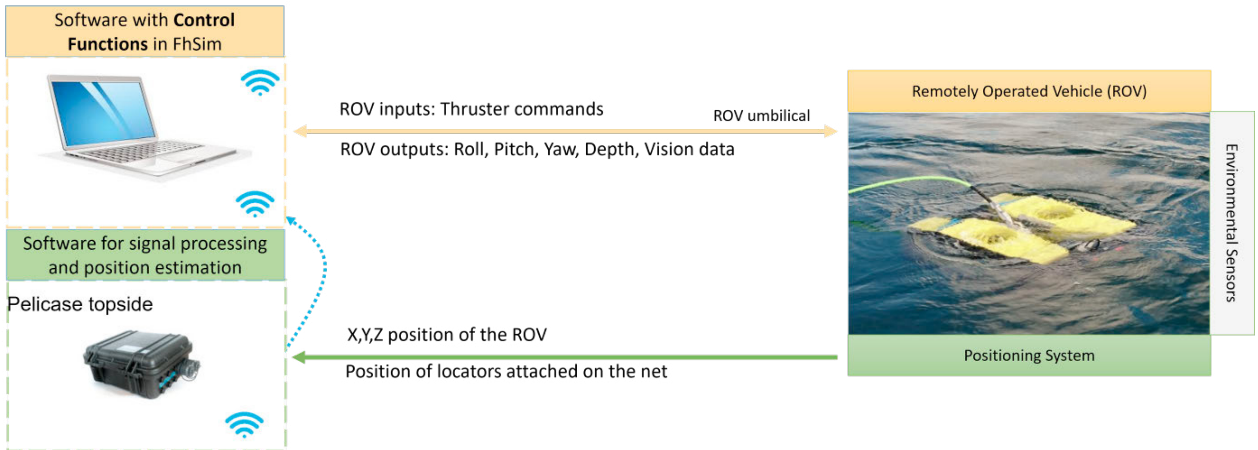


Fig. 3. Illustration of the full experimental setup during field trials.

showed that the positioning system was able to capture the positions of static and moving objects underwater with sufficient precision and accuracy to enable the implementation of autonomous control functions for the navigation of an ROV. For more details on the installation and the precision of the adapted positioning system, see Kelasidi et al. (2020); Su et al. (2021). The orientation and the depth of the vehicle was obtained from the IMU and depth sensor installed in the UUV.

During the experiments, the ROV was commanded to autonomously navigate in the fish cage in different patterns and collect high quality data from the installed sensors. The vehicle was set up to obtain vision data and environmental data such as light, temperature and oxygen levels inside the cage during the autonomous navigation using its onboard camera and sensors (Fig. 4). Measurements of the vehicle heading, depth and position were sent to an external computer where the full control framework was implemented in FhSim. Positions from the net were also relayed to the external computer to estimate cage deformations in real-time, thereby providing net positions to the control structure for each time step. Control actions were then calculated and sent via serial connection to the robot. The control gains were tuned in the field and the planned paths were set to keep at least 2 m from the net to avoid potential collisions and resulting damage to the net due to unexpected events. Velocity control was not implemented in these trials since estimation of velocities from position measurements would be noisy and there was no sensor for direct velocity measurements (e.g., DVL). Fig. 3 shows the experimental setup adapted during the full scale trials.

3.2 Experimental results

The results from the field trials are presented in this section, where the precision of the position measurements, the real-time structure deformation, the relative position of the ROV and the different paths of the vehicles during autonomous navigation are described, respectively. Pitch and roll were not controlled in the trials under the assumption that they are self stabilizing.

Precision of position measurements: Initial tests in both a controlled lab environment and in the field were done to evaluate the accuracy of the underwater positioning system. Fig. 5a and Fig. 5b present the measured positions of the ROV at the the Ocean Basin Laboratory (e.g., ROV resting on the tank bottom) and from the field trials (e.g., ROV on DP mode). The position measurements were shown to be stable and without any significant errors (e.g., jumping or loss of signals), indicating that the accuracy of the measured positions is well suited for testing and implementation of autonomous underwater operations in fish farms. Extensive investigations of these data and details can be found in Kelasidi et al. (2020); Su et al. (2021).

Structural deformation and relative ROV position: During the field trials, the method from Su et al. (2021) was used for real-time estimation of net cage deformations. Using a 10-minute moving average filter over measurement data collected over a period of 36 hours, the largest estimation error was 0.6 m, indicating that the method works well for real-time estimation of the shape of the net cage structure. The model is also able to estimate the direction and speed of ambient water current, which can further be implemented in autopilot functions that are able to compensate for current forces (See Su et al. (2021)). Fig. 6a and Fig. 6b show the comparison of estimated and actual positions of the net and corresponding current velocities from a simulation case study.

Path following: The ROV followed the reference for the straight line path with the North, East and Down positions following its references (Figs. 7a and 8a) with few deviations. Similarly, the ROV was also successful at autonomously navigating along the square path (Fig. 7b), as illustrated in Fig. 8b. Together, these results illustrate that the proposed control system is suitable for autonomous ROV navigation in fish cages. However, the control system did not consider the effects of water currents, which may be the cause behind the deviations seen in the square path case. This can be improved in the future by implementing integral action to compensate for water currents. As shown in Figs. 7c and 8c, although the ROV was able to follow a curved path, there was a constant error on the x-position, most likely due to an implementation error of the coordinate system for path planning and guidance which was not identical with the cage-referenced coordinate system. In the future, more general path following concepts will be demonstrated using the proposed general control framework.

Constant distance from net: The estimation model was also able to calculate the distance from the ROV to the net by using the estimated cage deformation and cage-referenced position of the ROV. Fig. 9a shows an example of the recorded horizontal positions of the ROV and the three locators on the net cage, where a DP controller (Fossen, 2011) was used to keep the ROV at a constant position during the first 40 s and then follow a straight

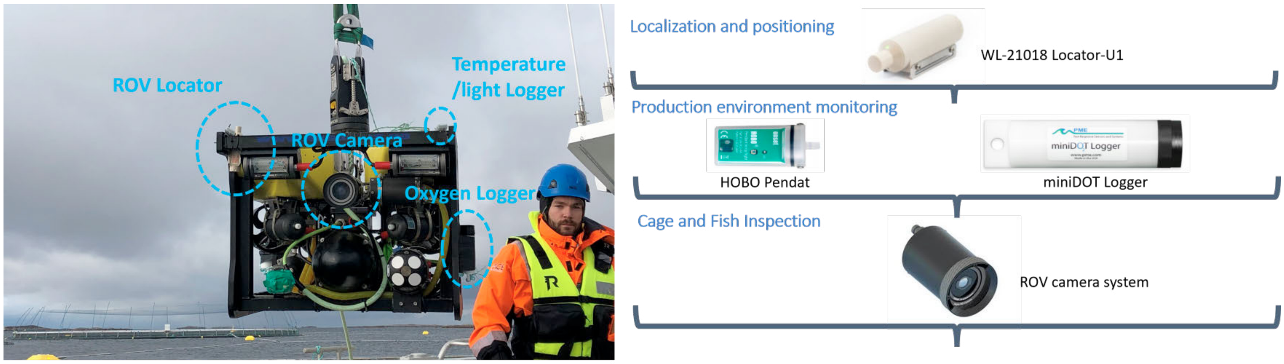
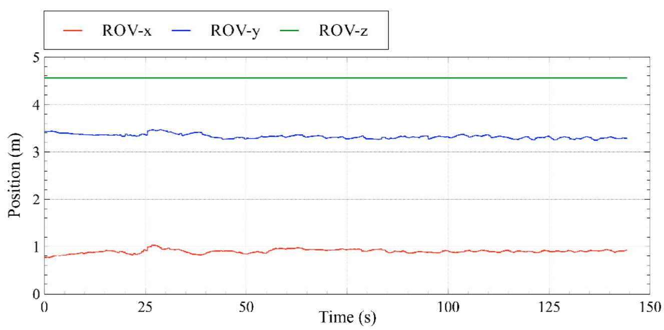
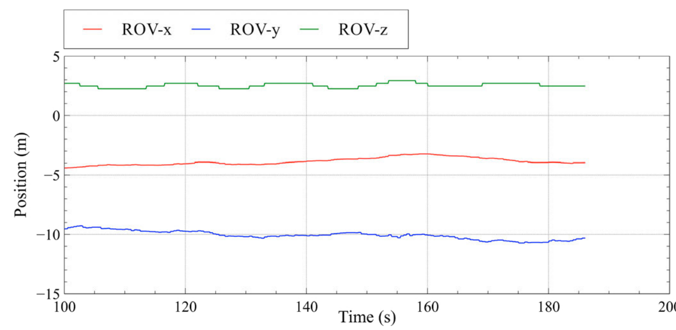


Fig. 4. Illustration of the integrated sensors on the Argus Mini ROV.

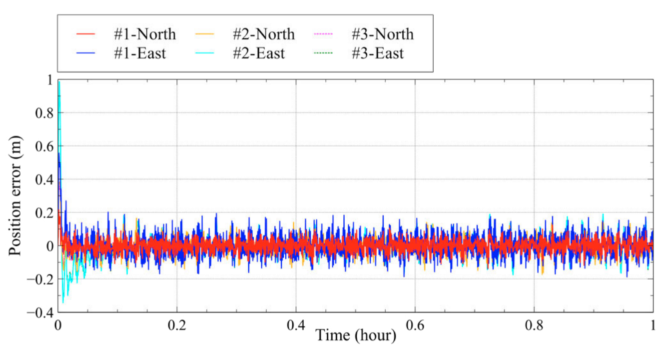


(a) Time series of the measured ROV positions (Lab)

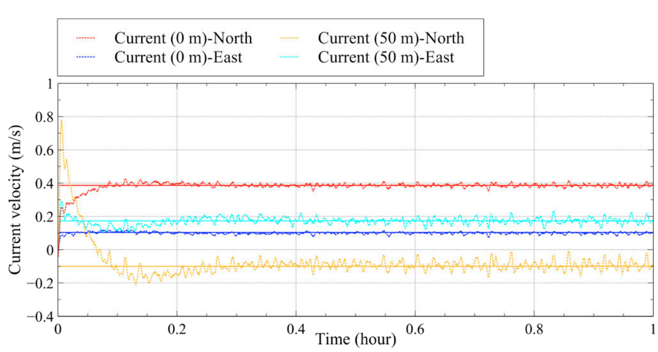


(b) Time series of the measured ROV positions (Field trials)

Fig. 5. Precision of position measurements of the ROV during experiments at laboratory and field trials.



(a) Comparison of estimated and actual positions of the net (presented as position errors)



(b) Comparison of estimated and actual current velocities

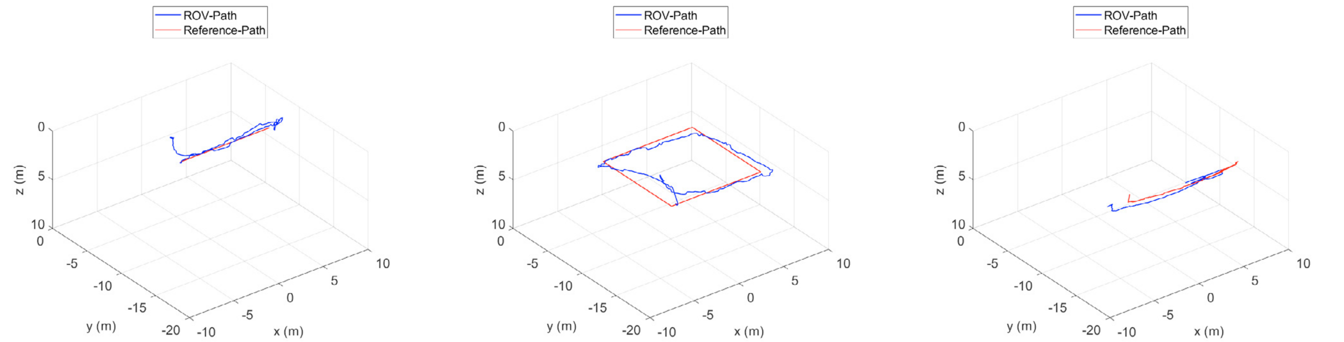
Fig. 6. Locator positions and current velocities.

line. The calculated distance from the ROV to the net (Fig. 9b, negative value since the ROV is inside the cage) reflects the same pattern in that it follows a straight line when maintaining a constant position. The distance then increases as the ROV moves along a straight line towards the center line of the cage parallel with the x-axis, where the distance reaches its highest value, before decreasing again as it moves beyond the center line. The accuracy of this result implies that the method performs well enough to enable autonomous net-following navigation when cage deformation is at steady-state.

High-quality data acquisition: During the field trials, data from underwater camera and environmental sensors were collected to assess the conditions of the fish, the structures and the environment. Data quality was investigated based on defined requirements, and subjected to machine vision methods (Schellewald et al., 2021) for the estimation of fish and cage-referenced distance and orientation. The obtained data could also be used for the evaluation of fish and cage conditions such as abnormal fish behaviour, physical injuries and wounds, feeding and feed waste, net inspection, quantification of biofouling and identification of holes. However, these tasks are beyond the focus of the present study, and should rather be the focus of future research efforts. Other data, such as oxygen, temperature and light conditions at different locations inside the cage were also collected with the overall goal to give better insight on what are the conditions that the fish experience. Extensive discussions and presentation of the obtained data and results can be found in Kelasidi et al. (2020).

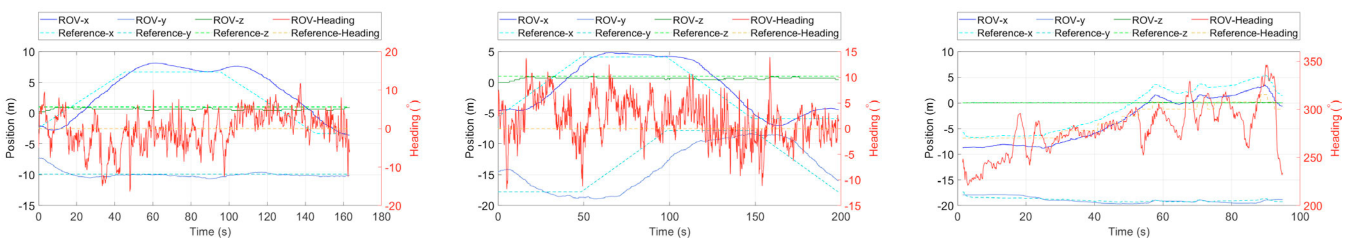
4. CONCLUSIONS AND FUTURE WORK

This paper presents a general control framework that extends and adapts the previous work on control strategies for UUVs and thus introducing a direct link between the motion of the UUV, fish behaviour and flexible structures. The capabilities of this new advanced control approach were demonstrated through experimental trials done in a



(a) Straight line path (at depth of 1 m) (b) Square path (at depth of 1 m) (c) Curved path (distance from net of 5 m)

Fig. 7. Path following case studies during autonomous monitoring and inspection operations in net cage. (Controller gains: $K_p = [20, 20, 100, 30]$ $K_p = [0, 0, 0.1, 0.1]$)



(a) Straight line path (b) Square path (c) Curved path

Fig. 8. Positions of the ROV for the cage studies investigated in Fig. 7.

full-scale field study, emulating inspection and monitoring operations in sea-based fish farms using UUVs. An underwater positioning system and integrated numerical model were found to be suitable for real-time estimation of cage deformation and ROV distance to the net. Based on this, an ROV equipped with vision and environmental sensors was able to autonomously navigate inside a fish cage and collect and analyze high quality data related to net deformation, fish condition and the production environment from the entire cage volume. The conclusion of this study is that permanent resident underwater vehicles with autonomous functionality can be used for different operations in sea-cages, and collect relevant data on fish and cage conditions on a daily basis. In the future, more advanced motion planning methods could be investigated in field trials and experimental results can be obtained to demonstrate the interaction between the UUV and the fish. Although he proposed method was developed for aquaculture purposes, the general control framework can be applied to other marine industries where one might encounter and need to interact with biological entities.

ACKNOWLEDGEMENTS

The authors would like to thank Water Linked AS, Sealab AS, Norsk Havservice AS and NTNU for their contributions to the CageReporter project activities.

REFERENCES

Amundsen, H.B., Caharija, W., and Pettersen, K.Y. (2022). Autonomous rov inspections of aquaculture net pens using dvl. *IEEE Journal of Oceanic Engineering*, 47(1), 1–19.

Antonelli, G. (2014). *Underwater Robots*. Springer Tracts in Advanced Robotics. Springer International Publishing, 3 edition.

Balchen, J. (1991). Possible roles of remotely operated underwater vehicles (ROV) and robotics in mariculture of the future. *Modeling, Idenntification and Control*.

Bjelland, H.V., Føre, M., Lader, P., Kristiansen, D., Holmen, I.M., Fredheim, A., Grøtli, E.I., Fathi, D.E., Oppedal, F., Utne, I.B., and Schjølberg, I. (2015). Exposed Aquaculture in Norway. In *MTS/IEEE OCEANS*.

Bjerkeng, M., Kirkhus, T., Caharija, W., T Thielemann, J., B Amundsen, H., Johan Ohrem, S., and Ingar Grøtli, E. (2021). Rov navigation in a fish cage with laser-camera triangulation. *Journal of Marine Science and Engineering*, 9(1), 79.

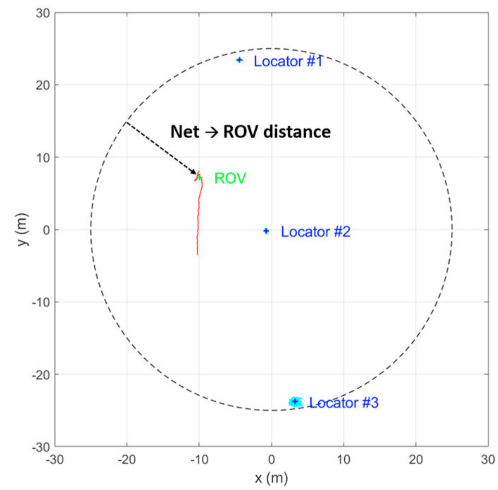
Caharija, W., Pettersen, K.Y., Bibuli, M., Calado, P., Zereik, E., Braga, J., Gravdahl, J.T., Sørensen, A.J., Milovanović, M., and Bruzzone, G. (2016). Integral Line-of-Sight Guidance and Control of Underactuated Marine Vehicles: Theory, Simulations, and Experiments. *IEEE Transactions on Control Systems Technology*, 24(5), 1623–1642.

Chalkiadakis, V., Papandroulakis, N., Livanos, G., Moirogiorgou, K., Giakos, G., and Zervakis, M. (2017). Designing a small-sized autonomous underwater vehicle architecture for regular periodic fish-cage net inspection. In *2017 IEEE International Conference on Imaging Systems and Techniques (IST)*, 1–6.

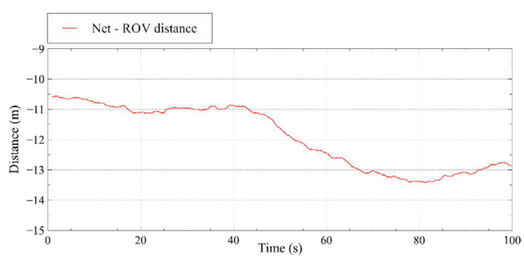
Endresen, P.C., Føre, M., Fredheim, A., Kristiansen, D., and Enerhaug, B. (2013). Numerical Modeling of Wake Effect on Aquaculture Nets. In *ASME 2013 32nd International Conference on Ocean, Offshore and Arctic Engineering*. American Society of Mechanical Engineers.

Enerhaug, B., Føre, M., Endresen, P.C., Madsen, N., and Hansen, K. (2012). Current Loads on Net Panels With Rhombic Meshes. *ASME 31st International Conference on Ocean, Offshore and Arctic Engineering*, 49–60.

FAO (2020). The state of world fisheries and aquaculture.



(a) Recorded horizontal positions of the ROV and the three locators on the net cage: mean position of the locator (green cross) and followed straight line by the ROV (red line)



(b) Time series of the calculated distance of the ROV to the net where the negative values indicate that the ROV is inside the cage

Fig. 9. Real-time relative position of the ROV.

Føre, M., Dempster, T., Alfredsen, J.A., Johansen, V., and Johansson, D. (2009). Modelling of Atlantic salmon (Salmo salar L.) behaviour in sea-cages: a Lagrangian approach. *Aquaculture*, 288(3/4), 196–204.

Føre, M., Dempster, T., Alfredsen, J.A., and Oppedal, F. (2014). Modelling of Atlantic salmon (Salmo salar L.) behaviour in sea-cages: Using artificial light to control swimming depth. *Aquaculture*, 388–391.

Føre, M., Fjåra, S., Ohrem, S.J., Kelasidi, E., Bloecher, N., and Amundsen, H.B. (2021). Adaptive motion planning and path following for permanent resident biofouling prevention robot operating in fish farms. In *OCEANS*.

Fossen, T.I. (2011). *Handbook of Marine Craft Hydrodynamics and Motion Control*. John Wiley & Sons, Ltd.

Føre, M., Frank, K., Norton, T., Svendsen, E., Alfredsen, J.A., Dempster, T., Eguiraun, H., Watson, W., Stahl, A., Sunde, L.M., Schellewald, C., Skøien, K.R., Alver, M.O., and Berckmans, D. (2018). Precision fish farming: A new framework to improve production in aquaculture. *Biosystems Engineering*, 173, 176–193.

Karlsen, H.Ø., Amundsen, H.B., Caharija, W., and Ludvigsen, M. (2021). Autonomous aquaculture: Implementation of an autonomous mission control system for unmanned underwater vehicle operations. In *OCEANS*.

Kelasidi, E., Liljebäck, P., Pettersen, K.Y., and Gravdahl, J.T. (2016). Innovation in Underwater Robots: Biologically Inspired Swimming Snake Robots. *IEEE Robotics and Automation Magazine*, 23(1), 44–62.

Kelasidi, E., Liljebäck, P., Pettersen, K.Y., and Gravdahl, J.T. (2017). Integral Line-of-Sight Guidance for Path Following Control of Underwater Snake Robots: Theory and Experiments. *IEEE Transactions on Robotics*, 33(3), 610–628.

Kelasidi, E., Su, B., Thorbjørnsen, E.S., Moen, E., Schellewald, C., Yip, M.H., Remmen, B.M., and Mulelid, M. (2020). Cagereporter - development of technology for autonomous, bio-interactive and high-quality data acquisition from aquaculture net cages. Technical report, SINTEF Ocean AS, Trondheim.

Kruusmaa, M., Gkliva, R., Tuhtan, J.A., Tuvikene, A., and Alfredsen, J.A. (2020). Salmon behavioural response to robots in an aquaculture sea cage. *Royal Society Open Science*, 7(3), 191220.

Lader, P., Dempster, T., Fredheim, A., and Jensen, Ø. (2008). Current induced net deformations in full-scale sea-cages for Atlantic salmon (Salmo salar). *Aquacultural Engineering*, 38(1), 52–65.

Livanos, G., Zervakis, M.E., Chalkiadakis, V., Moirogiorgou, K., Giakos, G.C., and Papandroulakis, N. (2018). Intelligent navigation and control of a prototype autonomous underwater vehicle for automated inspection of aquaculture net pen cages. In *IEEE International Conference on Imaging Systems and Techniques, IST*.

Moe-Føre, H., Endresen, P.C., Aarsæther, K.G., Jensen, J., Føre, M., Kristiansen, D., Fredheim, A., Lader, P., and Reite, K.J. (2014). Structural Analysis of Aquaculture Nets: Comparison and Validation of Different Numerical Modelling Approaches. *ASME 33rd International Conf. on Ocean, Offshore and Arctic Engineering*.

Oppedal, F., Dempster, T., and Stien, L.H. (2011). Environmental drivers of Atlantic salmon behaviour in sea-cages: A review. *Aquaculture*, 311(1), 1–18.

Reite, K.J., Føre, M., Aarsæther, K.G., Jensen, J., Rundtop, P., Kyllingstad, L.T., Endresen, P.C., Kristiansen, D., Johansen, V., and Fredheim, A. (2014). FHSIM — Time Domain Simulation of Marine Systems. *ASME 33rd International Conf. on Ocean, Offshore and Arctic Engineering*.

Ridao, P., Carreras, M., Ribas, D., Sanz, P.J., and Oliver, G. (2014). Intervention auvs: The next challenge. *IFAC Proceedings Volumes*, 47(3), 12146 – 12159.

Rundtop, P. and Frank, K. (2016). Experimental evaluation of hydroacoustic instruments for ROV navigation along aquaculture net pens. *Aquacultural Engineering*, 74, 143–156.

Schellewald, C., Stahl, A., and Kelasidi, E. (2021). Vision-based pose estimation for autonomous operations in aquacultural fish farms. *13th IFAC Conference on Control Applications in Marine Systems, Robotics, and Vehicles, IFAC-PapersOnLine*, 54(16), 438–443.

Su, B., Kelasidi, E., Frank, K., Haugen, J., Føre, M., and Pedersen, M.O. (2021). An integrated approach for monitoring structural deformation of aquaculture net cages. *Ocean Engineering*, 219, 108424.

Su, B., Reite, K.J., Føre, M., Aarsæther, K.G., Alver, M.O., Endresen, P.C., Kristiansen, D., Haugen, J., Caharija, W., and Tsarau, A. (2019). A multipurpose framework for modelling and simulation of marine aquaculture systems. In *International Conference on Offshore Mechanics and Arctic Engineering*. American Society of Mechanical Engineers.

Wu, Y., Liu, J., Wei, Y., An, D., Duan, Y., Li, W., Li, B., Chen, Y., and Wei, Q. (2021). Intelligent control method of underwater inspection robot in netcage. *Aquaculture Research*.