

Reducing risk in aquaculture through autonomous underwater operations

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Abstract:

Operation of fish farms offshore increases the need for autonomous operations, monitoring and decision support systems. Autonomous systems have different levels of self-governance and may reduce the direct physical human operator interaction in operations with the fish cages and tools. The objective of this paper is to present current work in a research project related to increased autonomy in underwater operations in Norwegian aquaculture. The main focus of the project is on risk management and simultaneous localization and mapping (SLAM) of underwater vehicles. The paper discusses how research from subsea oil and gas intervention and ocean monitoring, combined with the research work in the project, may contribute to improved risk control and risk mitigation for fish farm operators, the environment, and fish welfare.

Keywords: Aquaculture, Autonomy, Risk, Underwater Operation, SLAM

1. INTRODUCTION

In Norway, fish farming is one of the most dangerous occupations. The harsh weather conditions, a high manual workload, utilization of heavy equipment, as well as organizational factors, such as a high work efficiency pressure, contribute to the risk [1, 2]. Salmon and trout aquaculture started in protected coastal areas near shore, but nowadays fish farming has also moved into more exposed locations, due to conflicts in the local communities and space restrictions, as well as a need for better production facilities and reduced environmental footprint. In addition, the fish cages have grown considerable in size with more fish in each cage. The exposed fish farms create even more challenges related to the working environment for operators, due to worse sea states.

Operation of fish farms further offshore increases the need for autonomous operations, monitoring and decision support systems. Autonomous systems have different levels of self-governance and may reduce the direct physical human operator interaction operations with the fish cages and tools. Different levels of autonomy (LoA) describe detailed aspects of an autonomous system and operation, including operator dependency, communication structure, human-machine interface (HMI), an online risk management system, intelligence, planning functionalities, and mission complexity [3]. Advancing from a lower level automated system to a higher-level autonomous system is usually a gradual process. Currently, the fish feeding systems is one example of low level autonomous system (automated), as most often these are controlled remotely from a feeding barge. Another example is inspection, maintenance and repair (IMR), which are (underwater) operations performed in each fish cage or on the whole facility. When it comes to net inspections, divers or underwater vehicles (UV), i.e., remotely operated vehicles (ROV) are used. Net cleaning can be executed with high pressure cleaning rigs operated by cranes or ROVs. Several fish farming operations are performed manually, and currently there are no systems with a high autonomy level in use in aquaculture.

To ensure safe operations in the challenging work conditions, new and adapted methods that improve tools, technology and platforms in aquaculture with more autonomy are needed. The effects of more exposed and larger fish farms, and major biological, operational and environmental challenges, increase the need for efficient risk management and decision support. This is addressed in the research project “Reducing Risk in Aquaculture” [4]. The objective of this paper is to present current work in the research project related to increased autonomy in underwater operations in aquaculture. The main topics of the project are risk management and simultaneous localization and mapping (SLAM) to improve the

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autonomy of UV. The paper discusses how research results from subsea oil and gas intervention and ocean monitoring, combined with ongoing work in the research project, can contribute to better risk control and risk mitigation for fish farm operators, the environment, and fish welfare. The scope of the paper is the fish farm itself and its most important operations, which means that hatching, fish processing or transportation are not included.

The remainder of this paper is organized as follows: Section 2 introduces fish farming operations in today's sea-based fish farms. The associated risks that need to be considered during operations are described in Section 3. Section 4 presents underwater positioning in aquaculture. Section 5 discusses uncertainty in underwater positioning related to risk, and Section 6 discusses their potential integration. Section 7 states the conclusions.

2. NORWEGIAN AQUACULTURE

In 2016, Norwegian aquaculture produced 1,3 mill. tons of fish, mainly salmon and trout [5]. This amount has not changed much since 2012 [6], due to sustainability challenges. Still, the potential for growth has been estimated to be fivefold by 2050 compared to 2010 [7], but the industry lacks sheltered coastal locations and there are challenges with sea lice, fish escape and waste on the seabed close to the farms [8].

Salmon in fish farming is mostly hatched in freshwater tubs and tanks onshore. When the salmon is able to live in seawater, they are moved to a sea-based fish farm, where they remain for 14-22 months until they have gained a weight of around 4-6 kg. Then they are slaughtered and processed, before transported to the end user market [9]. Fish farms are constructed in different ways, but the most typical commercial farm consists of a fleet or barge surrounded by cages floating in the sea, each with a collar and net moored to the sea bottom. The trend towards moving fish farms offshore has led to the development of new concepts, of which some are influenced by the offshore oil and gas industry. Ocean farm 1 [10] is one example of such a concept, which was commissioned and put into operation in 2017.

Important operations in a fish farm are fish transfer, feeding and transport of feed, inspections of equipment, measurement of oxygen, cleaning of nets, removal of dead fish, delousing, health and biomass control, and inspections, maintenance and repair [11]. Several of these operations involve the use of service vessels, and heavy equipment, such as cranes and ROV, exposing the personnel to operational risk [12].

3. RISK IN AQUACULTURE

ISO 31000 [13] defines risk as the “effect of uncertainty on objectives”. An effect can both be positive and negative, but the scope of this paper focuses on potential losses. Further, it is stated that “risk is often expressed in terms of the consequences of an event and the associated likelihood of occurrence” Uncertainty is defined as “the state, even partial, of deficiency of information related to, understanding or knowledge of an event, its consequence, or likelihood”.

[14] state that two different events could have the same probability of occurring. The basis for establishing the probabilities, however, could be entirely different. [15] discusses a risk perspective constituted by:

$$\{a, c, q|k\} \quad (1)$$

The hazardous event is represented by a , consequences by c , uncertainty by q , whereas k is the background knowledge and basis used to determine a , c , q . Since uncertainty is closely linked to risk, rather than probability only, q is used rather than p to open for various quantitative and qualitative ways of expressing uncertainties [16].

Risk analysis identifies a set of events a' and consequences c' . $\{a, c'\}$ may be a collision between a UV and a fish net in a fish cage. c' are then the consequences to the environment, to the fish itself, and economic losses. q can be expressed by probabilities, but it may not necessarily include all uncertainties in assumptions and background knowledge. Hence, for autonomous systems operating in a challenging and unpredictable environment with limited or no a-priori information, q can be assumed to be high and k low. Uncertainty needs to be recognized and reduced by improving our knowledge basis [3]. The background knowledge k depends on available data, expert judgements and models representing different phenomena involved, and include assumptions, suppositions and the choice of models. In risk assessment, data for hazardous events and accident scenarios may be scarce, which means that a probability model is difficult to establish [15].

[17] suggest to consider five consequence dimensions of risk in aquaculture. These are risk to personnel, risk to material assets, risk to the environment, risk to fish welfare, and food safety. Risk to personnel focuses on risk to fish farm employees mainly. The main causes to fatalities are loss of vessel, man overboard and blow by an object [2]. Serious injuries are often due to blowing from objects, falls, and entanglement [1]. Risk to environment includes negative impact, such as waste/hazardous compounds on the sea bottom, escape of fish and genetic interaction with wild salmon [8, 18]. Before the standard NS 9415 was introduced in 2004, structural failures were a major cause to salmon escapes. A large-scale escape involves $> 10\ 000$ fish [18].

Risk to material assets consider potential damage to the fish farm structures and vessels. Risk to fish welfare includes impact on fish health, such as parasite infections. Sea lice infections reduce the fish health condition and may be transmitted to wild salmon under certain conditions, increase the consumption of medications, and may cause mortalities [19, 20]. The presence of sea lice and fish escape are the major environmental problems in salmon fish farming [21]. Every year, sea lice infections cost the industry around €1 billion [22]. Different countermeasures and delousing efforts exist, but they typically also cause hazards to fish health and welfare [23].

Food safety is related to safe consumption of salmon and potential impact on consumer's health. Heavy metals' toxicity has been raised as an issue of concern, but [24] showed that the levels of mercury, arsenic, dioxins, PCBs and DDTs in Norwegian farmed Atlantic salmon from 1999 to 2011 were below the EU maximum allowable limits. The requirements to salmon as food requires strict control throughout the production process, and Norwegian salmon is safe [25].

4. UNDERWATER POSITIONING OF AUTONOMOUS SYSTEMS IN AQUACULTURE

More exposed locations for aquaculture makes the use of remote control and underwater vehicles (UV) feasible for underwater operations. According to [26], ROV is an example of a tethered UV and can be enhanced with more autonomous functionality. Frequent inspections of the fish farm are important to prevent fish escapes and damage to equipment [18]. Diving can be hazardous and the use of manually operated ROVs is costly. The lack of high communication bandwidth in underwater environments means that tethered vehicles are necessary for live monitoring, which may be hazardous during operation in confined areas, such as in a fish cage, e.g., due to entanglements. A major challenge is to determine the position of the UV relative to its surroundings, especially due to currents and waves impacting and deforming the net structure [27, 28], in addition to the fish moving around in the cage.

Figure 1 presents a qualitative event tree for loss of position of a UV in aquaculture, including the consequences collision and successful recovery. A collision with the fish net, for example, may cause a hole leading to fish escape, affecting several of the consequence dimensions in Section 3, such as negative environmental impact, loss of reputation, and economic losses.

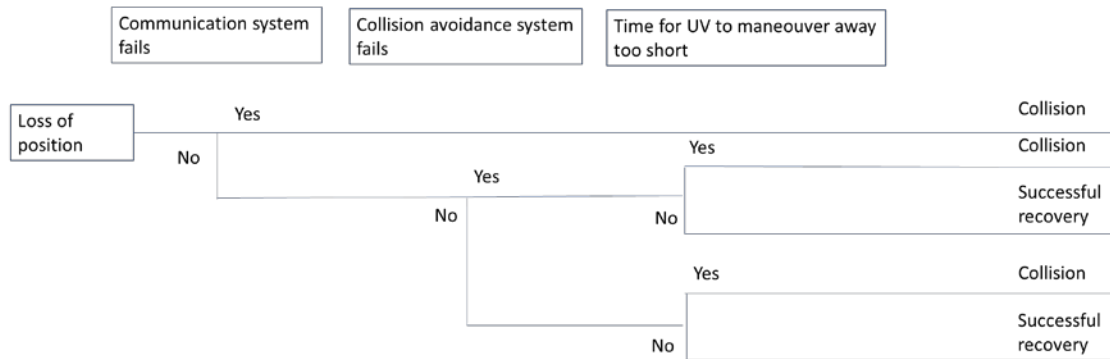


Figure 1. Event tree for loss of position of an UV in a fish cage, which may lead to collision with obstacles, such as ropes or fish net.

To utilize UV in aquaculture safely, there is a need for robust localization and positioning systems that are capable of estimating position relative to obstacles. Solutions can be based on vision or sonar sensors mounted on the vehicle, typically, along with Doppler Velocity Logger (DVL) and Inertial Navigation System (INS) for dead reckoning capability. This can also be combined with an acoustic transponder system located on the aquaculture structure. However, the configuration of an acoustic transponder system for range measurements is a key challenge [29]. Motion in near surface transponders may have a negative effect on the positioning system. Motion around a fish cage is caused by environmental disturbances from currents and waves, which may lead to errors in the position estimate. This type of error needs to be as small as possible for accurate positioning of the UV. Demanding weather conditions also create oscillations in the transponders if mounted near the surface.

Sandøy et al [30] has proposed an extended Kalman filter (EKF) solution, which includes an error dynamics model integrated in the pseudo-range measurement model. The paper suggests a procedure to identify the parameters in the error model, which has been experimentally tested in the marine cybernetics lab at NTNU. The results of the work show that the proposed EKF is able to compensate for the wave motion, decreasing the root mean square (RMS) errors compared to no compensation, providing more accurate localization.

Today, UVs in terms of autonomous underwater vehicles (AUVs) are mostly applied in open waters, and there are only a few examples of use in more confined environments. ROVs are used in more confined applications, including aquaculture, even though umbilical entanglement is a major concern [31]. A possible solution for localization could be to acquire a map of the fish net online and localize the UV relative to it. This solution is called simultaneous localization and mapping (SLAM) [32, 33].

Localization is about estimating a vehicle's location. The environment around the vehicle may be known, but not its location. Mapping means building a map, and SLAM does localization and mapping at the same time. SLAM may be less accurate than just localization when mapping is known. SLAM is fundamental for most navigation systems and is a fundamental problem for truly autonomous systems. SLAM is central to a range of indoor, outdoor, air and underwater applications for both manned and autonomous vehicles [32]. SLAM has become increasingly popular in underwater navigation [34], but nobody has investigated underwater SLAM in an aquaculture environment. Work in the Reducing Risk in Aquaculture Project [4] is ongoing to develop SLAM, using sonar for range and bearing measurements to obstacles.

5. UNCERTAINTY IN UNDERWATER POSITIONING FROM A RISK PERSPECTIVE

5.1 Uncertainty in risk assessment

In probabilistic risk analysis, a distinction may be made between aleatory or stochastic uncertainty and epistemic uncertainty. The former refers to variation in a population of similar items, and may be

represented by a probability distribution, for example the Gaussian with mean μ and variance σ^2 . Aleatory uncertainty may be illustrated by the rolling of a dice. The probability p_i is the fraction of outcomes with i .

Epistemic uncertainty is caused by lack of knowledge k , which means that it may be reduced if more knowledge becomes available. This is also called subjective uncertainty. Other issues that contribute to uncertainty in risk assessments are complex systems, tightly coupled systems, new technology, software intensive systems, dynamic systems, and system interaction with the environment. These issues make it difficult to reveal all relevant hazardous events. In addition, model uncertainty, parameter uncertainty, consequence uncertainty, calculation uncertainty, uncertainty due to time pressure and wrong/missing competence may affect the results of the risk assessments. Hence, it is challenging to take uncertainties into consideration sufficiently in risk assessment [35]. Still, risk analysis may become more valuable with higher uncertainty [36].

5.2 Uncertainty and the risk perspective in underwater operation in aquaculture

There is uncertainty in a UV's motions and observations. Motion increases the uncertainty of the system. The main issue in probabilistic underwater robotics is to estimate the state of the vehicle from sensor data. The vehicle has to rely on its sensors to estimate its state, i.e., the position and orientation. Sensor measurements may be influenced by noise and outliers and this may result in uncertainty in the estimation of the vehicle state. Probabilistic state estimation calculates belief distributions over potential states.

The state of the vehicle is characterised by different dynamic and static aspects variables related to the environment and the vehicle itself. Examples are pose, velocity, sensor functioning or not, the location of obstacles around, etc. The future state of the vehicle at time t can be denoted x_t . The previous state is denoted x_{t-1} . Measurement data at time t are denoted z_t , whereas control input is denoted u_t . The state and measurements can be considered to be determined by probabilistic laws and conditional probabilities of previous states and measurements given by:

$$p(x_t | x_{0:t-1}, z_{1:t-1}, u_{1:t}) \quad (2)$$

A belief distribution assigns a probability to possible states based on the previous state posterior, i.e., a prediction, before including the measurement at time t , which is called the correction or measurement update. This is the main principle of the Bayes filter algorithm [32].

In SLAM, the vehicle path and map are unknown and the map and pose estimates are correlated. The mapping between observations and map, however, is unknown. Selecting the wrong data associations can have severe consequences (divergence). [32] show how the errors in the localization and mapping are represented by probability theory. This can be further exploited in the use of SLAM in aquaculture.

In risk analysis, Bayesian analysis is a common tool in which Bayes's theorem is used to update the representation of the epistemic uncertainties in light of new data to obtain the posterior distributions [37]. Hence, the current inclusion of uncertainty in SLAM algorithms has a narrower interpretation than in risk analysis according to Eq. 1, but improvements in SLAM should consider uncertainty in a wider sense.

In general, a mission planning algorithm for a UV takes into account the state of the vehicle when developing its guidance law. Ideally, for positioning and localization of an underwater vehicle, there should be perfect knowledge k of the state and no uncertainty. This means that the UV would know its position correctly, as well as the location of the goal. Further, all actions executed by the UV would have perfectly predictable outcomes c' . In practise, however, error will accrue during the UV's execution of actions, and the ocean environment is unpredictable and unstructured, further contributing to deviations in the UV's position and path, even with sensor based reactive control to make adjustments.

Hence, there will always be risk involved in the UV operation, but consideration of risk defined according to Eq. (1) is currently not an integrated part of vehicle guidance and control. Traditionally, the anticipated uncertainty associated with robots are calculated in terms of probabilities for each decision outcome ($p(a)$), represented by frequentist probabilities. However, with such an approach, important aspects of risk are ignored, since:

- Consequences c are not explicitly considered, but are linked to the vehicle's decision outcomes in terms of deviations in the optimal path only;
- Hazardous events a only include the vehicle's decisions and deviations from the path, not potential technical failures related to the condition of the vehicle and environmental disturbances;
- The probability of a decision outcome $p(a)$ could be a poor prediction of the actual consequence c given that a occurs;
- The knowledge k supporting the probabilities could be strong or wrong and may change during operation.
- The probabilities do not cover risk influencing factors (RIFs). A RIF can be defined as "an aspect (event/condition) of a system or an activity that affects the risk level of this system or activity". If a RIF is not possible to measure directly, there is a need for an operational definition of the RIF [38].

Some of the above-mentioned aspects are discussed on a generic basis in [39]. The risk perspective and the challenges related to underwater operation in aquaculture is illustrated in Figure 2. The figure shows that there is considerable risk involved with UV operation in aquaculture, which is necessary to incorporate in positioning and localization algorithms developed for UV operating in aquaculture.

In Figure 2, one may assume that the hazardous event a is loss of position and q is the uncertainty about the localization of the UV (ROV). The consequences c' may change depending on where the ROV is located: collision with ropes in the middle of the fish net (at time ($T = t - 1$)) may lead to other consequences c_{t-1} than collision with the fish net itself, i.e., c_t (at time ($T = t$)). In addition, the uncertainty q changes, depending on the accuracy and type of positioning system and the type and quality of sensors. Since the fish net moves with waves and currents, it may be more difficult to determine the distance to the fish net with sufficient precision at time ($T = t$) than at time ($T = t - 1$). Hence, the uncertainty q_t increases, the consequence c_t becomes more severe, and, depending on the sensors available, our knowledge basis k_t may decrease; i.e., the risk increases from time ($T = t - 1$) to time ($T = t$).

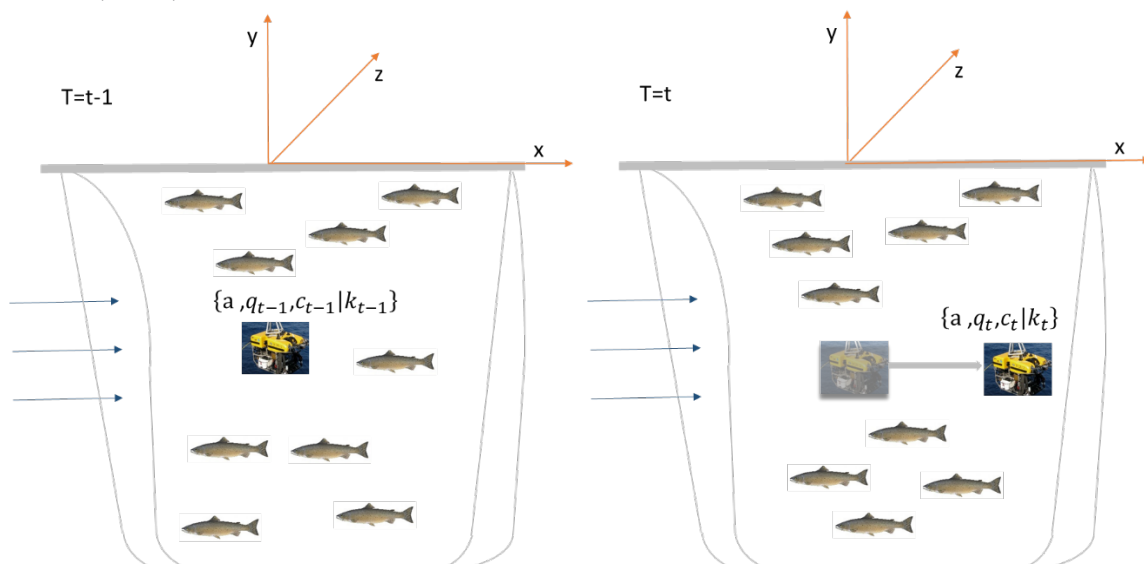


Figure 2. Illustration of fish cage with a flexible net, which is exposed to sea current. The ROV is moving inside the cage from the middle towards the fish net.

6. A CONCEPTUAL DISCUSSION OF IMPLEMENTATION OF A RISK PERSPECTIVE IN UNDERWATER POSITIONING IN AQUACULTURE

A potential integration of the risk perspective (Eq. 1) would be an extension and potentially an improvement to SLAM. This might be done in different ways, as presented in the following.

6.1. Risk based path planning in aquaculture

Currently for a robot, uncertainty q is considered in terms of frequentist probabilities p , and updated when new information becomes available (measurements z). When a UV selects its actions, it is driven by goal achievement. In addition, it might be of interest to minimize “cost” in terms of time, consumption of energy, or number of collisions. Such trade-offs can be expressed by use of value functions [32].

According to [40], expected value decision-making is not adequate for low probability, large uncertainty, and high consequence events. Two hazardous events may be represented by probability distributions with the same expected values, but they may be centered differently, which means that risk mitigation should focus on different decision strategies. Hence, there may be a need for including risk aversion considerations, which may be implemented by expected utility theory. The challenge, however, is to express a utility function useful for risk management decisions [41].

According to [42], a direct approach to risk control of an AUV is path planning adaptation. In particular, this is relevant for AUV inspection tasks, for which the hazardous event collision is important to consider (cf. Figure 2). Such an approach may provide advantages compared to existing methods for path planning, which mainly optimize the minimal cost or operational time. [42] proposes a hierarchical approach with risk integration, in which a mapped environment with known obstacles is assumed. The starting and ending position, in addition to weighting of different criteria of relevance for path planning, can be considered by the AUV itself, enhancing autonomy. The criteria can be determined based on RIFs, for example, those included in the nodes in the risk model for underwater operation in aquaculture, shown in Figure 3.

The approach in [42] can be applied for autonomous underwater operations in aquaculture, if a dynamic environment is included. In addition, since data computation capacity may be limited, the proposed approach may be desirable. Figure 2 shows that the risk related to position loss changes during UV operation in the fish cage. Figure 3 shows that position loss is influenced, for example, by changes in the risk factors (e.g., current).

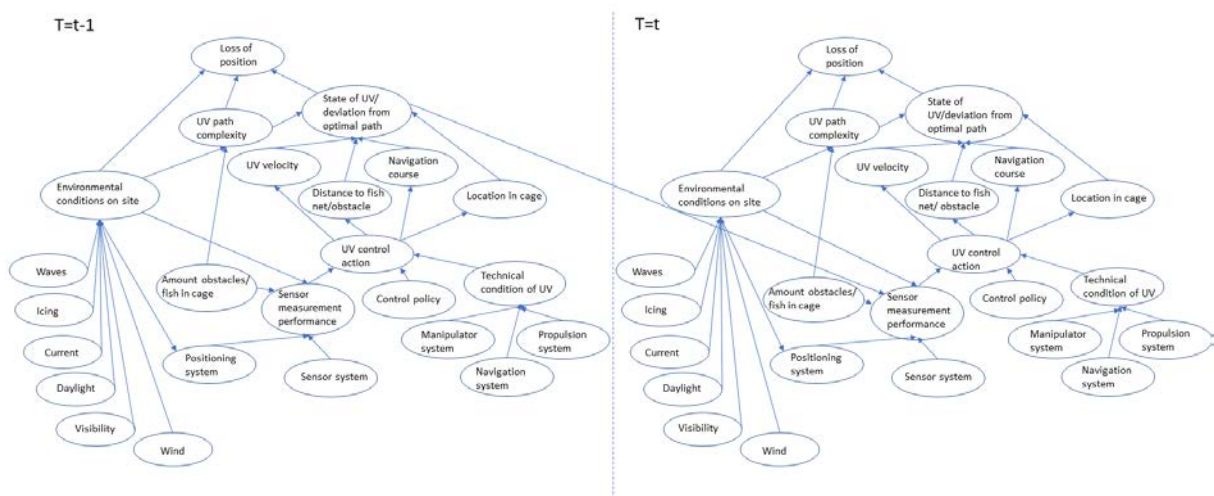


Figure 3. Qualitative BBN/influence diagram of underwater operation in aquaculture with nodes and RIFs related to the probability of loss of position of the UV for two different time instances.

6.2. Risk-based operational envelopes as decision support tool

For a UV, collision with obstacles may in some cases not be so critical. Colliding with a rope may lead to entanglement and mission abortion. The outcome is downtime and delays in the operation, with potential economic losses. Collision with the fish net, as mentioned earlier, is much more critical. Hence, the control policy of the UV should be able to take this issue into account, i.e., precise localization and navigation becomes more important the closer the UV is to the fish net. One solution supporting a human supervisor of a UV may be to implement operational envelopes surrounding the UV, providing decision strategies based on COLREG and TCAS rules, cf. [43].

[43] propose to use the Octree method for developing a static safety envelope for autonomous ROVs in subsea oil and gas operations. A safety envelope is defined as “a 3D spatial area around the underwater vehicle forming a virtual protective barrier (in space and time) against collision with known and unknown obstacles in the subsea environment (...)”. [43] presents a static safety envelope, which means that the size of the envelope is constant and does not change during operations. This approach may be feasible when a UV is operating close to the fish net, but when moving around in the fish cage, a dynamic envelope would provide improved risk information.

[44] propose a dynamic safety envelope, which enables the UV to decrease or increase the obstacle detection area. A fuzzy inference system (FIS) is utilized to vary the size of the safety envelope, depending on three fuzzy input variables; i.e., vehicle velocity, probability of acoustic sensor failure and time to collision. Risk based operational envelopes would be desirable in aquaculture, which means that it should be linked to a risk model, e.g., a dynamic BBN, cf. Figure 3, which would be an expansion of the three input variables used by [44].

The approach of [44] may be useful in aquaculture, but there may be different RIFs and safety requirements compared to subsea oil and gas intervention, for example with respect to safe distance to obstacle. A moving fish net may require more conservative constraints to distance than a fixed subsea production system (SPS) on the sea bed. The former may also be more vulnerable than a SPS. On the other hand, a thorough inspection means that the UV needs to get relatively close to the fish net to provide sufficient condition data.

6.3. Risk based localization

Figure 3 shows (risk) factors influencing the likelihood of position loss at two different time instances. When the nodes are quantified with probabilities, the risk model may become a dynamic BBN. Sensitivity analysis can be performed to identify the most important nodes or RIFs in the BBN, and then uncertainties related to these nodes can be assessed. If uncertainties are found to be high, this can be reflected in terms of weighting of the nodes, which impact their effect on the end node (position loss). Figure 1 and Figure 3 combined may represent the accident scenario of loss of position for an UV, including RIFs and causal relationships (Figure 3) and potential consequences (Figure 1). It is rather obvious that the risk perspective (cf. Eq. 1) is not considerably catered for in current SLAM for UV operation in aquaculture.

When using estimation filters for control, several underlying assumptions are made. Firstly, for Gaussian filters, the assumption about the feasibility of using the Gaussian distribution to express the uncertainty of the state of the underwater vehicle is made. Referring to the above discussion, uncertainties are only to a limited extent possible to express by a probability distribution. The limitations related to the sensor quality and the measurements may be known, and these may vary for different environmental conditions. In addition, as mentioned above, such limitations may be more severe under some circumstances than other.

Implementation of the risk perspective in Eq. (1) into the control policy of the UV could start in terms of using a strength of knowledge scale, as shown in Table 1. In addition to assessing the basis for the assumptions made related to the development and choice of control policy, algorithms, parameters,

operating context, the quality of sensor measurements and data models, (left column in Table 1), the level(s) of autonomy in the operation also impact the background knowledge. Complexity, for example, in terms of previous experience with the operation, influences the ability for sufficient planning of the operation and successful performance during operation with the different LoA. Complexity could be explicitly incorporated into Table 1.

In the example proposed in Table 1, the lowest “score” in any of the two columns determines the final “score”. For example, achieving “good” in column 1 (data and information quality) and “low” in column 2 (LoA) result in a final “score” of “low”. This judgement will be qualitative and is obviously dependent on the assessor. LoA is included as it is assumed that a human operator or supervisor will influence the background knowledge, k .

Table 1. Strength of knowledge scale, including LoA. Adapted and developed from [3], [45].

Data and information quality	Level of autonomy (LoA)
Good: All of the following conditions are met: Good and reasonable assumptions. Reliable and relevant data/information from measurements are available. Agreement among expertise in area. Models used are known to give predictions with sufficient accuracy.	Low: Human operator in charge or human supervisor may easily take over control and intervene efficiently.
Medium: <i>Aspects that are in between high and low.</i>	Medium: It is uncertain whether the human supervisor have sufficient time and ability to take over control and intervene.
Weak: One or more of the following conditions are met: Strong simplifications in assumptions. Very little reliable data or information available. Disagreement among expertise in area. Relevant and accurate prediction models do not exist.	High: Human supervisor will not be able to take over control and intervene in a timely and efficient manner.

A risk matrix, as shown in Figure 4 visualizes how the assessment of background knowledge, k , can be combined with probability. In Figure 4, red is unacceptable, yellow is ALARP, and green is acceptable, corresponding to the as low as reasonable principle (ALARP). For more on ALARP, see, e.g., [46]. The hazardous event a considered in this example is position loss. A score corresponding to medium for k in Table 1 and using probability (medium) as a measure for q (without defining the scale here), means that the hazardous event ends up in the ALARP region.

Strength of knowledge, k	Uncertainty measure q : Probability of occurrence				
	High	Medium - high	Medium	Medium low	Low
High	Red	Yellow	Yellow	Green	Green
Medium	Red	Red	Yellow (x)	Yellow	Green
Low	Red	Red	Red	Yellow	Yellow

Figure 4. Risk matrix for k and q .

When assessing the potential consequence (collision with fish net, aborted operation, entanglement), we end up with a risk in the high category, shown in Figure 5, meaning that we get an unacceptable risk related to that type of event.

Consequences/ Impact c	Uncertainty $u(q, k)$		
	Unacceptable	ALARP	Acceptable
High	Red	Red (x)	Yellow
Medium - high	Red	Yellow	Yellow
Medium	Red	Yellow	Yellow
Medium - low	Yellow	Yellow	Green
Low	Yellow	Green	Green

Figure 5. Risk matrices combining q and c .

The matrices in Figure 4 and 5 have been developed based on [47], but are further adjusted and adapted to UV for aquaculture. The outcome of implementing considerations into SLAM, as addressed in Table 1 and Figures 4 and 5 is that the UV should be able to determine when the localization is influenced by so much uncertainties that loss of position is likely, in particular when the consequence may be collision with the fish net. In short, the UV should be able to know when the risk is too high, and mission should be aborted.

7. CONCLUSION

This paper addresses challenges related to improved autonomy in underwater operations in aquaculture, which is particularly relevant when fish farms move further offshore. Enhanced autonomy is relevant for current fish farming operations, but with larger fish farms offshore, increased monitoring, remote control, supervision, and intelligent decision support systems are even more needed. Autonomous systems have different levels of self-governance and may therefore decrease the direct physical human operator interaction operations with the fish cages and tools, potentially reducing risk and improving cost efficiency.

This paper focuses on improved risk management and simultaneous localization and mapping (SLAM) for aquaculture, which are two research areas of particular importance to realize improved autonomy in exposed aquaculture operations. The paper outlines three different work areas for closer integration and implementation of a risk perspective in SLAM, namely; (i) Risk based path planning, (ii) operational envelopes as decision support tool, and (iii) risk based localization. The concept of operational safety envelopes from subsea oil and gas linked with dynamic risk modelling may be relevant for underwater operations in aquaculture. Uncertainty regarding risk influencing factors (RIF) is affecting the performance of an underwater vehicle (UV), which is necessary to take better into account in path planning and positioning and control of the UV in aquaculture.

Further research work will focus on implementation to evaluate effects on algorithm precision, and different filters will be investigated. It may also be necessary to consider trade-offs regarding the potential for “higher costs” related to improved precision in calculations and algorithms, and reduced risk in underwater operations.

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