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Context-based and image-based subsea pipeline degradation monitoring

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Abstract
This research examines the factors contributing to the exterior material degradation of subsea oil and gas pipelines monitored with autonomous underwater systems (AUS). The AUS have a role of gathering image data that is further analyzed with artificial intelligence data analysis methods. Corrosion and potential ruptures on pipeline surfaces are complex processes involving several competing elements, such as the geographical properties, composition of soil, atmosphere, and marine life, whose eflt in substantial environmental damage and financial loss. Despite extensive research, corrosion monitoring and prediction remain a persistent challenge in the industry. There is a lack of knowledge map that can enable image ausing an AUS to recognize ongoing degradation processes and potentially prevent substantial damage. The main contribution of this research is the knowledge map for increased context and risk awareness to improve the reliability of image-based monitoring and inspection by autonomous underwater systems in detecting hazards and early signs of material degradation on subsea pipeline surfaces.

Keywords Autonomous underwater systems · Image-based monitoring · Subsea pipeline degradation

1 Introduction

Material degradation of a pipeline can result in structural failures that endanger marine life, create environmental hazards, and cause significant financial losses. Understanding the factors contributing to corrosion is essential for understanding the development of corrosion in materials, building anti-corrosion structures, and making risk assessments during monitoring and inspection operations [1]. Several factors contribute to the deterioration of pipeline surface material, and there are multiple factors to consider when identifying the most effective ways to predict deterioration and ultimately prevent substantial damage. The most visible factors are the materials used to construct pipelines and geographical elements such as soil, environment, climate, and marine life. Complex processes affecting material degradation, corrosion, and eventual surface ruptures pose a challenge to industry and are the subject of continuous research.

Autonomous Underwater Systems (AUS), such as autonomous underwater drones and intelligent sensor systems, play an increasingly important role in the monitoring and inspection of remote, potentially chemically contaminated offshore structures, such as pipelines [2]. In the context of autonomous systems, autonomy characterizes self-organizing and self-sufficient systems to achieve a specific task [3]. The industry is increasingly relying on AUS for enhanced safety in remote operations. Missed opportunities in detecting damages at offshore structures, such as ruptures and gas leaks,

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can lead to catastrophic consequences for employees at connected facilities, the environment and significant financial losses. There is a growth in the usage of artificial intelligence (AI) and machine learning (ML) methods for continuous data and image analysis as the application and interest in AUS for monitoring and inspecting offshore infrastructure grows. However, for reliable data analysis, the AUS requires extensive use of empirical data and causal reasoning [4, 5]. There is insufficient labeled data to train ML algorithms for detecting hazardous events. Even more so, the methods lack context in distinguishing significant information from insignificant and hence reliably responding if and when the situation requires it. Commonly, an absence of visibility and contextual knowledge of the operation hinders image-based analysis. Therefore, a knowledge map must be established to determine the most effective and reliable means to plan operations and aid AUS in monitoring and inspecting critical infrastructure.

The main contributions of this paper are:

- Analysis of the different factors, geographical properties, soil composition, and marine life in the context of autonomous pipeline monitoring and inspection.
- Mapping of domain knowledge for context-based and risk-informed autonomous monitoring of subsea pipeline material degradation.
- Proposal of a strategy for reconsidering how image-based analysis using AUS is used for safety purposes and overcoming the shortcomings of AUS operations is proposed.

In Sect. 2 of this paper, we review literature by examining different aspects of pipeline material degradation and monitoring, such as the development and types of corrosion, geographical properties, marine life at anthropogenic structures, and potentials in image-based pipeline monitoring. In Sect. 3 we wrap up the different aspects of pipeline degradation monitoring and form a knowledge map of competing dimensions for a more reliable image-based monitoring of pipelines with autonomous underwater systems. In Sect. 4 we propose rethinking the image-based monitoring, inspection and adaptive sensor scheduling based on the operation-specific context. Finally, Sect. 5 includes summary of the paper, concludes the paper and highlights future work.

2 Literature review

2.1 Pipeline material degradation

Pipeline material degradation, such as corrosion, which can lead to material rupture or cracking, has a significant economic and ecological impact, consuming 4% of the gross domestic product of industrialized countries [6]. Due to the significant reliance on pipelines for product transportation, the offshore oil and gas industry is the most impacted. Subsea pipeline degradation is a complex process involving a series of causes and events [7]. Despite extensive research and prevention systems, corrosion remains one of the industry's most significant challenges. Corrosion can cause damage to both the inside and exterior layers of a pipeline and image-based inspection by AUS allows for the detection of exterior corrosion. Hagarova et al. [8] examined the types of corrosion and prevention mechanisms that often involve coatings and cathodic protection. The outer surfaces of pipelines are additionally protected by protective barriers, metal and non-metal coatings, glass fiber, rubber, and epoxide designed to last for the duration of the pipeline's life [7–9]. However, the degradation of the outer surface of the pipeline gains an electrochemical nature. The exterior corrosion highly depends on the soil's chemical composition, the water's salinity in the environment, the existence of currents and atmospheric characteristics, and the presence of microorganisms [8]. Additionally, the surrounding soil influences aeration, affecting water content, oxygen concentration, and other potentially corrosive constituents. While sandy soil acts as a type of protection for pipeline materials, clay-rich soil creates a more corrosive environment. Corrosion damage of gas pipelines is often divided into following categories:

- Sweet corrosion occurs due to CO_2, H_2S, S, H_2O, inorganic salts, chlorides, sand and bacteria in transported products.
- Sour corrosion develops in H_2S environment that becomes corrosive in water-gas environment and can cause cracking in the pipeline wall.

- Microbially influenced corrosion is caused by microorganisms, bacteria, fungi, and other biological growth that produce waste material, such as acids, CO_2, H_2S, which increase the toxicity and promote corrosiveness of the environment.
- Corrosion cracking is induced by mechanical damage that occurs under the component of stress and corrosive environment.

In addition, carcasses of animals and other animal deposit on the pipelines contribute to the increased microbial presence and promote further material degradation.

2.2 Geographical properties and pipeline degradation

The physical features of soil significantly contribute to the corrosion propagation of buried metals, which is particularly apparent in pipelines. Wang et al. [1] perfromed the soil corrosivity tests that most commonly analyze oxidation potential, pH factor, water content, and salt saturation. According to the National Association of Corrosion Engineers and the American Society for Testing and Materials, the degradation process of pipeline materials is considerably determined by soil resistivity and corrosivity [1]. Additionally, the authors [1] examined data mining, artificial intelligence, and machine learning approaches to analyze large amounts of sensor-collected soil data and determine soil composition and corrosivity. They observed that this strategy, despite being practical, had significant limitations:

- Soil properties are fixed and cannot be easily changed to fit the conditions on the field. This limitation can be attributed to the need for more context challenges of AI and ML approaches.
- Assessing the soil's corrosivity is a complex task that often involves contradictory factors. During the data analysis with AI and ML methods, the contradictory problems presented by the interaction of multiple factors and the inconsistent effects on soil corrosion need to be sufficiently addressed.
- The lack of specificity in the classification of soil corrosivity contributes to the expansion of uncertainty, necessitating more information from the observations.
- Image data plays a vital role in detecting and analyzing corrosion on subsea pipeline surfaces.

Addressing these limitations would facilitate the prediction of the material degradation levels and improve the monitoring of the rate of material degradation development.

Ohaeri et al. [7] examined climate as another important component of material degradation. They single out the cold environment as a challenge to metallic materials and as one of the primary causes of brittleness, especially in welded areas that lose ductility. The common idea is that materials are less susceptible to corrosion in colder climates, primarily due to the ice covering or permafrost in buried pipelines, which prevents oxygen from accessing surface material [7]. However, high salinity inhibits the freezing process and accelerates corrosion. Similarly, chloride-enriched water and ice create a corrosive environment. Hydrogen is another challenging component contributing to the accumulation of faults and eventual failure in metallic materials. The authors [7] argue that there is not a single factor that contributes to the material degradation of subsea pipelines but rather a series of events that contribute to accelerated material failure, making it vital to observe each event to predict the pipeline life-cycle.

2.3 Marine life at subsea anthropogenic structures

Various attempts have been made to determine the positive and negative effects of pollution and corrosion from offshore structures on the behavioral patterns of opportunistic species [10–15]. The mutual impacts of opportunistic organisms and subsea anthropogenic structures, such as offshore oil platforms, can be summarized in two focus areas:

1. the impact of material degradation and associated pollution from offshore constructions on opportunistic species
2. the impact of opportunistic species on offshore structural materials

Both focus areas provide vital information about the behavioral patterns of opportunistic species in connection to certain pipeline surface materials during degradation (i.e., corrosion, ruptures), and associated pollution. Some species can be the cause of pipeline degradation, while others significantly increase or decrease their appearance when material degradation already occurs [12]. Although the microbial species that cause material degradation, i.e., corrosion, are not visible with image-based inspections [10], many species that appear or disappear under higher saturation of elements in the environment as a result of degradation or pollution are not microorganisms and are visible with imaging equipment. As a result of the elevated components in the environment produced by material degradation of offshore infrastructure, the appearances or disappearances of specific species are frequently classified as either positive indications or negative indicators of pollution [12]. Positive indicators, also known as tolerant opportunistic species, flourish in environments with elevated levels of components produced by material degradation (i.e., increased number of species due to higher saturation of iron in the environment due to corroded material). Negative indicators are species with low tolerance whose disappearance from an area may indicate pollution, or elevated saturation of components produced by material degradation, such as corrosion [12]. Even though positive indicator species thrive in polluted environments, some of them are dependent on the existence of negative indicator species. This dependence leads to a reduction of positive indicators due to the decrease of negative indicators.

Successful observation of opportunistic species around offshore structures is supplemented by information about soil, sediments, seasons, and weather conditions. Su et al. [13] explored the mutual influence of corrosion and microbial communities on buried petroleum pipelines. They argued that soils with distinct microbial populations can have varying effects on the corrosion of buried petroleum pipelines. Their research centered on three distinct types of soil exposed to varying levels of corrosion and petroleum pollution. The authors [13] were able to determine, using electrochemical measurements, that the microbial diversity in soil surrounding corroded pipelines decreased independently of the extent of petroleum contamination. However, electrochemical testing also revealed a more significant concentration of microorganisms that degrade hydrocarbons. Dubiel et al. [10] examined microbial composition in corrosion-surrounded environments and found that such environments considerably modify the microbial composition in the soil and that carbon steel or iron corrosion correlates with sulfate loss in the environment.

Different microbial communities inhabit different soil types, further influencing the observed area's benthic communities. Seasonal context is vital in determining if an increase in larvae in the water contributes to murkiness and invites other species to feed, leading to poor visibility and necessitating varying contextual and sensor inputs for the AUS. Similarly, storms and similar weather conditions can contribute to murkiness in shallower water and sediment deposits. This kind of contextual knowledge can aid in eliminating common issues of AI methods, particularly anomaly detection, pattern recognition and classification, such as biases, an inclination towards efficiency, and a lack of causal and contextual knowledge. While pattern recognition detects patterns or regularities in data, anomaly detection is responsible for detecting data points that do not conform to the data patterns, irregularities, or anomalies [16]. The ability to distinguish between important and irrelevant anomalies is a crucial challenge when using anomaly detection methods to identify potentially hazardous conditions on pipeline surfaces.

2.4 AUS and image-based pipeline monitoring

Image-based monitoring and inspections of structures offshore with mobile cameras that are attached to drones or with stationary cameras attached to structures, can produce extensive collections of image data [17]. Autonomous operations on offshore structures rely on AI for real-time or near-real-time data analysis of extensive image data collections. Detecting material degradation on images of subsea pipelines typically requires computer vision methods, pattern recognition, or anomaly detection. As corrosion and ruptures may be examined through differences in color and texture of the material surface, anomaly detection is a common approach to detect when these changes occur in comparison to the expected appearance of pipeline surface during monitoring operations.

Idris et al. [9] reviewed pipeline inspection using an image-based system for corrosion detection. Through images and videos, a visual examination of pipeline surfaces aids in detecting corrosion by observing changes in texture and color. The following forms of corrosion are classified by appearance and can be detected with image analysis [9, 18–23]:

1. Uniform or general corrosion that is evenly distributed across materials.
2. Pitting corrosion, a localised corrosion that leads to small ruptures in metallic materials.
3. Crevice corrosion is one of the most harmful corrosion types that forms inside of ruptures, or spaces and seals.
4. Galvanic corrosion occurs when a metal contacting another conducting, often protective material, results in corrosion, potentially leading to quick deterioration of materials.
5. Erosion-corrosion occurs due to mechanical action, liquids or other particles that can form cavitation.
6. Intergranular corrosion, or stress corrosion, occurs at structural level of the metallic material.
7. Environmentally assisted cracking, including corrosion fatigue, hydrogen damage, and stress-corrosion cracking.

The authors [9] decomposed the problem of incorrect inspection results into underlying causes using a problem tree, as illustrated in Fig. 1. Each image contains a considerable amount of data, most often noise, making it challenging to select the meaningful data we may be searching for. A substantial amount of sensor-collected data is lost, and retrieving lost data in images is more feasible than other analog signal data. The authors [9] explain the process through a correlation between the lost pixels and their neighbors to retrieve the lost image compression. As Fig. 1 illustrates, a combination of challenges makes the incorrect image analysis result. The image processing step of image analysis suffers from a lack of information, inexperienced conclusions, wrong data interpretation, challenges derived from artificial intelligence, false data extraction, and undetected defects. Image enhancement layer challenges include poor quality, blur, over-exposure, focus, illumination, environmental constraints, and inappropriate tools and procedures.

Todd et al. [14] performed a review of utilizing remotely operated vehicles (ROV) responsible for collecting the data by observing offshore structures, but not autonomously inspecting the collected images. They found the ROV data collected near offshore anthropogenic structures to be a reliable and readily available information source for researches to further observe and analyze not just offshore structures but also marine life. The authors [14] observed that certain marine animals are taking advantage of the anthropogenic structures due to the growing microhabitat. This result indicated that repeated sightings of specific species can tell us about the microhabitats growing around structures and may signal an ongoing material deterioration or pollution surrounding the structures.

2.5 Degradation probability under corrosive events

Each instance of pipeline deterioration, such as external corrosion, may not be the result of the most common causes of such deterioration. Nevertheless, the likelihood that certain factors contribute to corrosion more than others can be determined by observing multiple risk assessments of corroded pipelines. The chemical composition of the soil and water (i.e., salinity, saturation of CO_2, H_2S), subsea atmospheric characteristics (i.e., currents, harsh environment), and the presence of microorganisms are the most common causes of corrosion [8]. To obtain the level of influence of corrosion-causing events through probability analysis, Yang et al. [24] examined numerous risk assessments, accident reports on corroded pipelines and values assigned by domain experts based on their subject knowledge and experience. Table 1 describes the probability of corrosion-causing natural factors, excluding human error or faulty sensors. The prior probability of an event is the probability that is assigned before data is considered. Whereas, the posterior probability is obtained with the new event or given the data observations. The prior probability, *P(U, E)*, is used to calculate the posterior probability, *P(U|E)* described by Eq. 1, when new data, an observed event or evidence supports the prior hypothesis, where *U* are all the data variables, and *E* represents the specific event [24], also listed in Table 1.

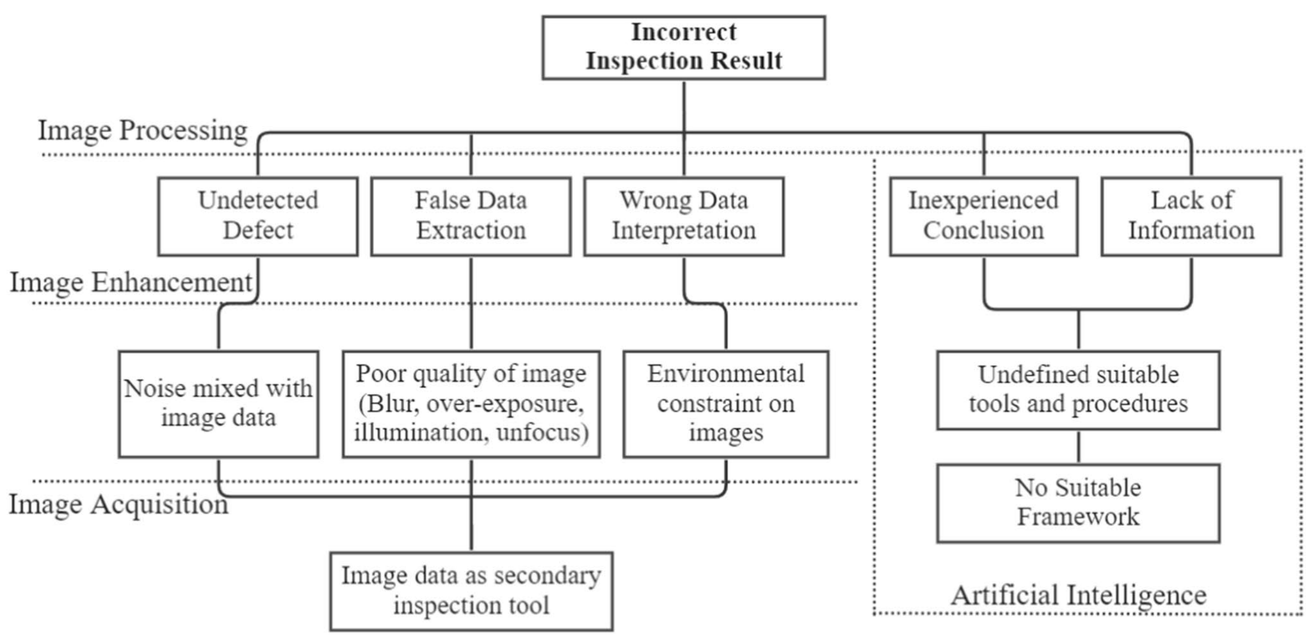

Fig. 1 Image-based inspection problem analysis [9]

Table 1 Probability of corrosion caused by common corrosive events, adapted from [24]

Event	Prior probability	Posterior probability
High salinity	3.35E–03	1.01E–01
Low temperatures	8.63E–04	2.60E–02
Microorganism presence in the environment	1.30E–03	3.91E–02
Microorganisms on corroded material	2.15E–03	6.47E–02
Anti-corrosive coating failure	6.20E–02	4.73E–01
High CO_2	5.00E–03	1.31E–01
High H_2S	7.15E–03	1.88E–01
Presence of sand in pipeline	5.00E–03	4.40E–02
Internal stress	5.50E–03	4.84E–02
External pipeline stress	2.70E–03	2.38E–02
Deposits or unclean pipeline	1.00E–02	1.07E–02
Harsh subsea environment	1.00E–03	1.19E–02

$$P(U \mid E) = \frac{P(E \mid U)}{P(E)} P(U) \tag{1}$$

Table 1 shows prior probability that represents what was initially believed prior to an event, whereas posterior probability is used to revise a prior belief when new information or an event becomes available. Prior and posterior probabilities are also used to estimate the risk of a hazardous occurrence, such as corrosion, by updating the probability of the default state based on previous observations. For machine learning applications, prior and posterior probability are useful in the training phase where posterior probability is updated after each training round. Knowing prior and posterior can enhance contextual understanding of the ongoing operation and facilitate more reliable and confident decision-making for AUS when new events or observations are encountered.

3 Context-based AUS operations

Monitoring, inspection, and intervention operations at offshore structures [2], are characterized by substantial amounts of sensor and image data collection and require intensive work with uncertainties and probabilistic data that can be a task too challenging for human operators. The AUS enables us to turn this data and heavy processing into information ready for interpretation. This data analysis is increasingly reliant on AI methods, such as ML and computer vision, that ease our understanding of ongoing operations and act as decision-support systems. AI connects several traditionally separate disciplines in its life-cycle, data analysis, model building, and software engineering as crucial components of autonomous systems [25]. More specifically, AI systems include problem definition, data collection through sensors or other data inputs, data conditioning, algorithm selection, and solution deployment or delivery as typical steps for developing AI models [25]. Finally, a vital part of the AI model is the Human–Machine Teaming element that represents interactions between humans and the system (i.e., user inputs, results checking, and aided decision-making). Because of the lack of training data and complexity of the tasks that AI systems are expected to accomplish, the efficiency and accuracy of outputs are often prioritized over interpretability and reliability [26]. Hence, unsupervised and black-box algorithms have become prevalent. These algorithms are often not application specific, challenging to interpret, integrate any risk assessment tasks into, and consequentially cause safety, ethical and moral concerns [26]. Additionally, available training data determines the settings in which classification and anomaly detection methods operate [27]:

1. Supervised: labeled dataset is available to train the model.
2. Semi-supervised: a dataset that does not contain anomalies is used to train the model on distinguishing anomalous from non-anomalous data instances.
3. Unsupervised: there is no available dataset for training the model. The model relies on determining statistical patterns between data instances.

Due to the lack of training data and the difficulty of reliably integrating unsupervised methods, AI approaches may be supplemented with heuristics-based methods or heuristic knowledge. Heuristics are described as decision-making methods that employ past experiences to generate quick and efficient solutions to a given problem [28–30], derived from heuristic knowledge that represents the expertise of domain specialists or experts. The systems that take advantage of heuristic knowledge, known as expert systems, serve as decision-support systems and are based on "what-if", "if-else" premises or fuzzy logic [28, 29]. The integration of heuristic or empirical knowledge of domain experts, in terms of rules in computing systems, show a great potential in formalizing human knowledge and drawing inferences from observed data for computationally low-cost decision making. However, the integration of heuristics alone into a system may result in biases based solely on past events. Integration of heuristics and analytical tools through AI is therefore one method for avoiding experience bias. Integrating human knowledge by managing heuristic expertise and storing essential skills in dependable and permanent systems can further enhance the interpretability of highly complex systems [30, 31]. For subsea pipeline monitoring, the incorporation of domain expertise may help provide operational context with operation-specific information, thereby enhancing the reliability for detection of anomalies or hazards on pipelines. This can be accomplished with risk assessment insights at the training level of the AI life-cycle or during the validation phase of the results, in which the detected anomalies are validated in order to discard noise or discover information about dangerous events. Integration of domain expertise is particularly critical due to recent efforts in AI standardization and functional safety requiring the use and development of more interpretable models that contain operational or application context and carry a high level of reliability. The safety of operations and decision-making systems for AUS cannot be overemphasized. Hence, the interest in integrating risk and context into these systems is increasing in research and industry [32–36]. In Fig. 2, we propose additional two components to AI models, context and supervisory components as a response to the recent challenges in industry and recommendations for a more standardized approach to AI systems [4, 37]. According to [37], a supervisory component or supervisory function, acting as a safe subset of the action space, is advised and expected to be a part of the architecture of AI systems. The AI outputs and decision-making processes are limited by this component, which is regarded as a non-AI component. The proposed context component includes operation-specific knowledge from the domain experts and anticipated risks. The impact of uncertainty on objectives is referred to as risk by [38], and it is typically referred to in terms of risk sources, potential events, likelihood, and consequences. Since AI systems are expected to perform detailed tasks, implementing these systems cannot remain generalized. Context gives us an idea of what kind of setting the AUS operation will take place in. In order to help the AI system decide whether a detected occurrence is significant, Fig. 3 elaborates on the context and expectations in the AI model for a particular operation. It does this by gathering all the relevant components of the decision-making process. Additionally, Fig. 3 illustrates the AI system, that includes image inputs and other sensor measurements contributing

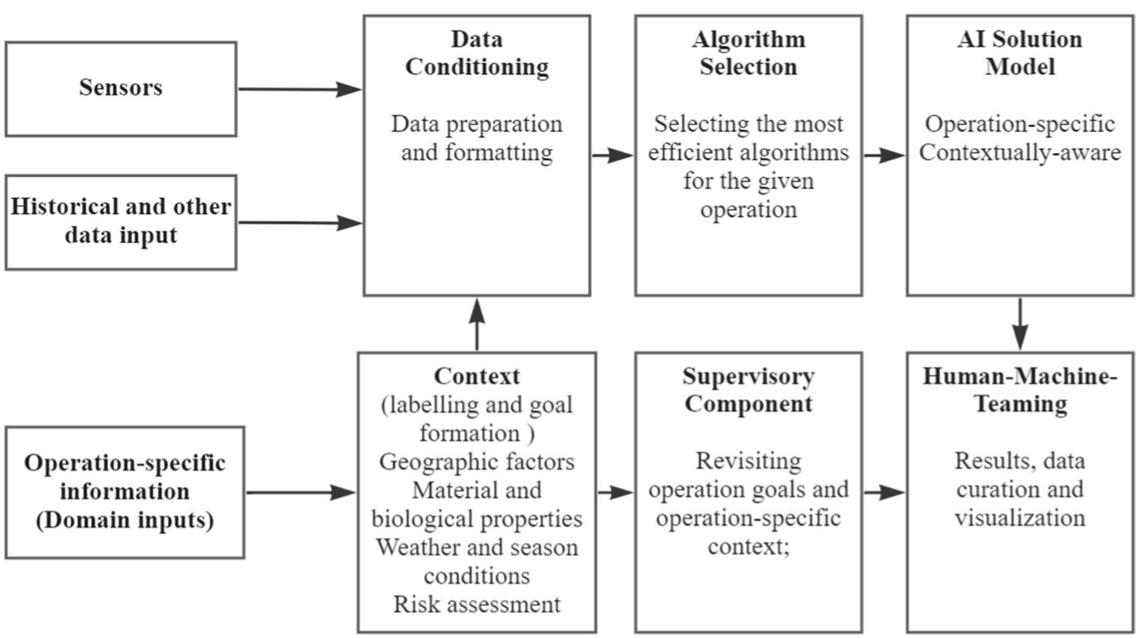

Fig. 2 AI model architecture

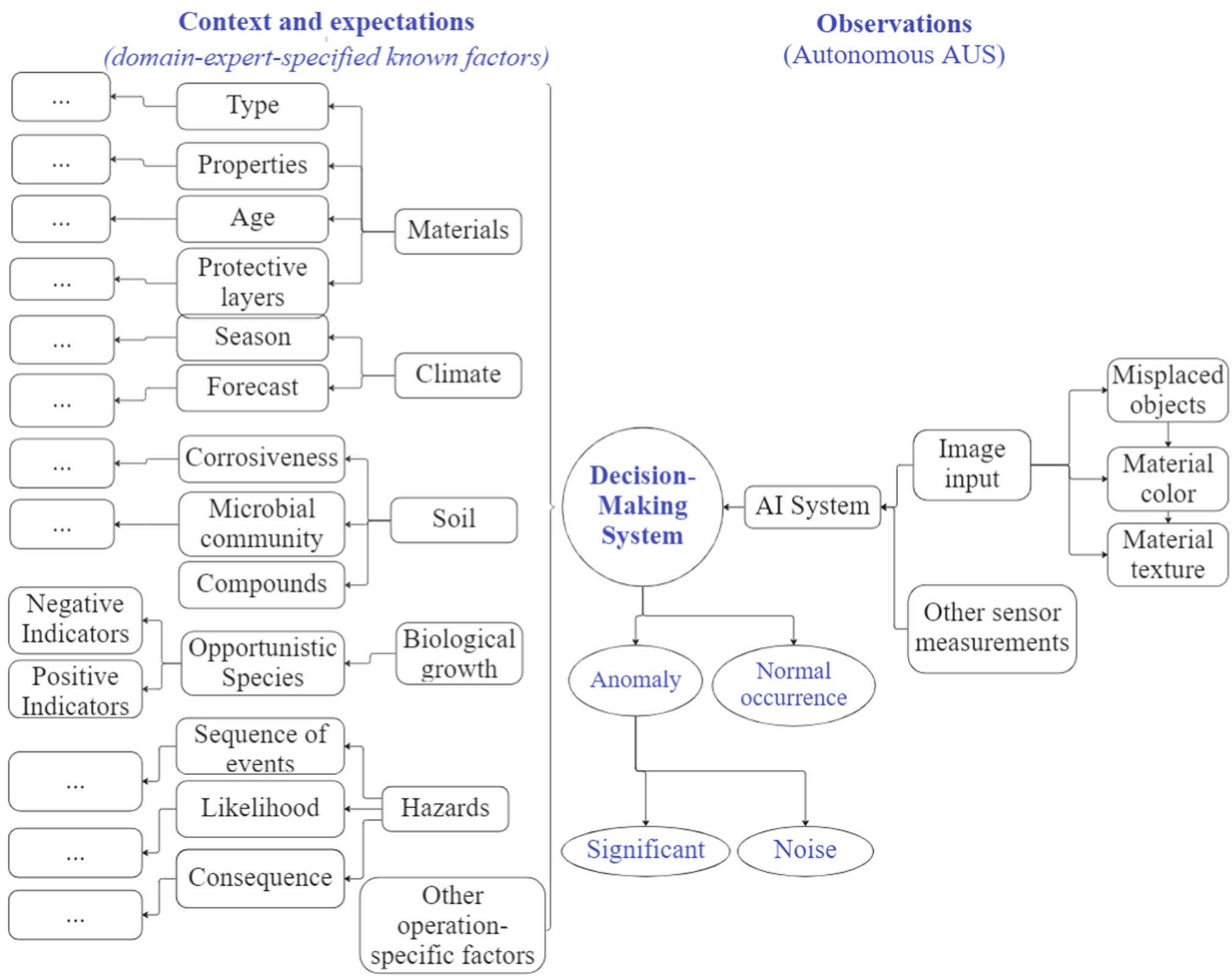

Fig. 3 Knowledge map for AUS pipeline inspection decision-making system

to decision-making system in detecting significant anomalies from noise, aided by context component. The context includes geographic characteristics like the soil's composition, the climate, the expected marine life and how it might alter in behavior, the material's observed qualities and the several kinds of corrosion that image-based monitoring and inspection makes it feasible to see. On the other hand, the risk assessment picture provides us with information about the risks that we can expect from the operation and lists potential hazards as sources of harm [38, 39]. It also shows us how likely it is that each of these things will occur as well as their consequences.

Flage et al. [40] observed the risks through the ways the risk emerges. They describe the emerging or emergent risk as a familiar or unfamiliar risk that becomes apparent in unfamiliar conditions. The authors link the definition of emerging risk to the known/unknown taxonomy derived from the press briefing by United States Secretary of Defense, Donald Rumsfeld [40]:

> There are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns—the ones we don't know we don't know.

From this taxonomy, Flage et al. [40] proceeded to address the unknown-knowns and the unknown-unknowns as ambiguous types of risks and link them to the events that lie outside of expectations, known as black swan events.

By observing the concept of emerging risks, we propose constructing a Rumsfeld matrix for AUS explorations, as shown in Fig. 4 and demonstrated on Fig. 5. In the matrix, we place the common challenges from underrepresented data available to the AI model by which AI may derive biased conclusions, known as data biases. An example of a bias

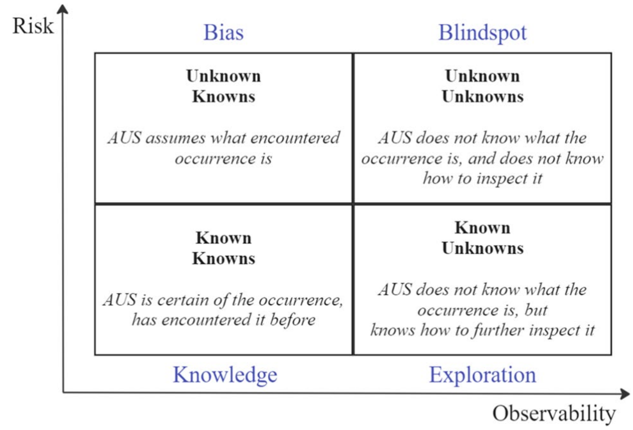

Fig. 4 Rumsfeld matrix for AUS exploration

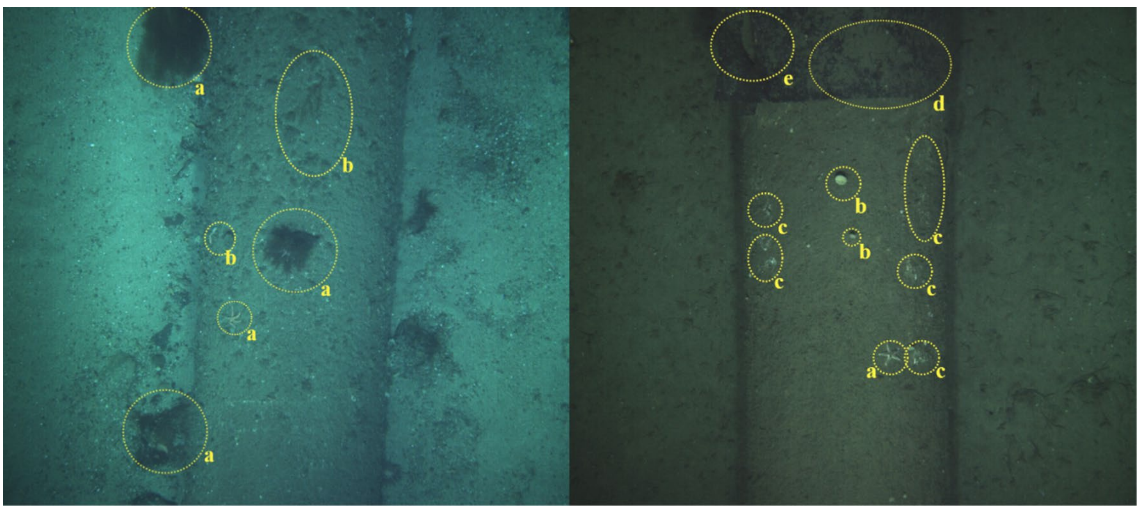

Fig. 5 Subsea pipeline images captured by an underwater drone: **a** Known known—Biological growth; **b** Known known—Sediment deposits; **c** Known known—Minor texture/color irregularities; **d** Known known—Major texture/color irregularities; **e** Known Unknown—material rupture. Photo: Equinor

in anomaly detection methods is sacrificing anomalies for efficiency and misclassifying them as noise due to a learned experience that there is a higher likelihood of encountering noise rather than a hazardous occurrence [39]. We link the possible situations during the AUS exploration to the emerging risks and identify the following:

1. **(Known-known) Knowledge:** AUS is certain of encountered occurrence because it has learned it from previous experience. The accuracy is high, confirmed by the supervisory component. Example of a known-known during pipeline inspection: AUS can accurately classify an encountered object, such as biological growth, damage, large boulder, with high confidence.
2. **(Known-unknown) Exploration:** AUS is uncertain of the encountered occurrence, but due to previous experience, knows to inspect the situation further to make the classification. Example of a known-unknown: AUS cannot confidently classify an encountered object, possibly due to the object sharing similar features with more than one classes, such as biological growth and sediment deposit that share the same color and shape.
3. **(Unknown-known) Bias:** AUS assumes the encountered occurrence and proceeds to classify it without further inspection, contributing to unintended bias and potentially problematic conclusions. Example of an unknown-known during pipeline inspection: AUS has not encountered a degraded ship anchor during training phase, but due to high similarity to a known class of biological growth in color and shape, AUS classifies the anchor as biological growth with high confidence, possibly putting the pipe at risk of being damaged due to vicinity of a heavy object.
4. **(Unknown-unknown) Blindspot:** The AUS does not know what the encountered occurrence is, does not know how to proceed in further inspecting it, or experiences challenges in the decision-making process necessitating human

interaction. Example of an unknown-unknown: AUS encounters object that is not known and cannot proceed to classify it, potentially requiring human interaction or resulting in an error. This situation may occur if the encountered object is extremely rare and unexpected, or has never appeared in any form during AUS training phase.

Figure 5 demonstrates an example of the object classification on the pipeline surface. The image is captured by an underwater drone where the common (known) occurrences, such as biological growth and expected benthic species (Fig. 5a), are identified, together with texture changes (Fig. 5c, d) and sediment deposits (Fig. 5d). Finally, a sudden material change resembling a material rupture necessitates further inspection (Fig. 5e). The AUS may need to analyze more images or use more sensor inputs during a subsequent inspection. Determining the right kind of sensors to utilize in a particular situation is crucial when image analysis is insufficient.

4 Rethinking image-based monitoring and inspection

Widespread use of sensors and imaging equipment for intelligent automation have increased the need for effective and adaptive sensor scheduling, a dynamic sensor control based on environment or operation needs to maximize the efficiency of existing sensors for the intended benefits [41]. Image quality is one of the main drawbacks of image-based analysis. Although many difficulties are camera-related (such as overexposure and focus), the environment can also provide a variety of problems that recur in patterns. During the inspection of offshore pipelines, the oil and gas industry anticipates highly autonomous systems to combine data from multiple sources for the most efficient and reliable data collection [2]. Rather than relying solely on images obtained from visible-spectrum sensors and cameras, it can be beneficial to incorporate data fusion from multiple imaging systems operating in different wavelength ranges, such as infrared cameras. The operation-specific context, however, may assist in identifying the additional types of sensors that may be the most effective under conditions where image-based inspection is problematic. The context of the operation is essential to assessing the validity of conclusions reached by AUS during an image-based pipeline inspection, as was shown in the preceding section. For each factor influencing the objectives of the inspection, such as material degradation, a conditional analysis might be required. Knowing the marine life cycle in such settings is highly beneficial, as a high larval density may lead to a high species density and poor visibility. Not only is it crucial to rely on various sensor inputs in situations when this is an expected pattern, but it is also crucial to avoid mistaking an increase in species presence for an anomalous occurrence. Similarly, in situations when the pipeline's surrounding soil is primarily clay, there is a higher likelihood of corrosion at the points where the soil contacts the pipeline and accumulates on the surface. Similar is true if the encountered occurrence creates ambiguity for an AUS and low confidence in analyzing the situation.

Figure 6 shows a high-level flowchart for entrusting image-based inspection after image quality analysis, illustrating a situation in which an image-based analysis may require additional sensor inputs to classify encountered occurrences during the inspection. An image's quality can be evaluated based on the anticipated conditions, such as exposure, blur, focus, and lighting, after it has been captured by imaging equipment like a drone camera. Object classification begins if the image quality is acceptable and the objects are visible enough for the analysis. Suppose the object is unknown or not identified by the AI model; in that case, the model returns to additional sensor inputs like temperature, pressure, and water content to gather more information. The same sensors are considered if the photos are of poor quality, and object analysis could be more reliable. The AUS needs more inputs to provide observation results if other sensor inputs supply more data to conclude the ongoing observation. Suppose the additional sensor readings are sufficient to support further analysis; in that case, the analyzed output should be updated with the operation-specific contextual information provided in the context component to generate observation results.

5 Conclusion and future work

This research reviewed different factors contributing to subsea pipeline surface material degradation, corrosion, and potential ruptures. The significant factors contributing to the degradation include geographical properties, such as climate and weather variables, soil and water components, microbial communities, and marine species as pollution indicators. Despite extensive study, corrosion continues to be a severe concern to the offshore oil and gas industry, with the potential to cause material failure, which can cause environmental disturbances and substantial financial losses. The employment of autonomous underwater systems for offshore structure inspections, such as intelligent

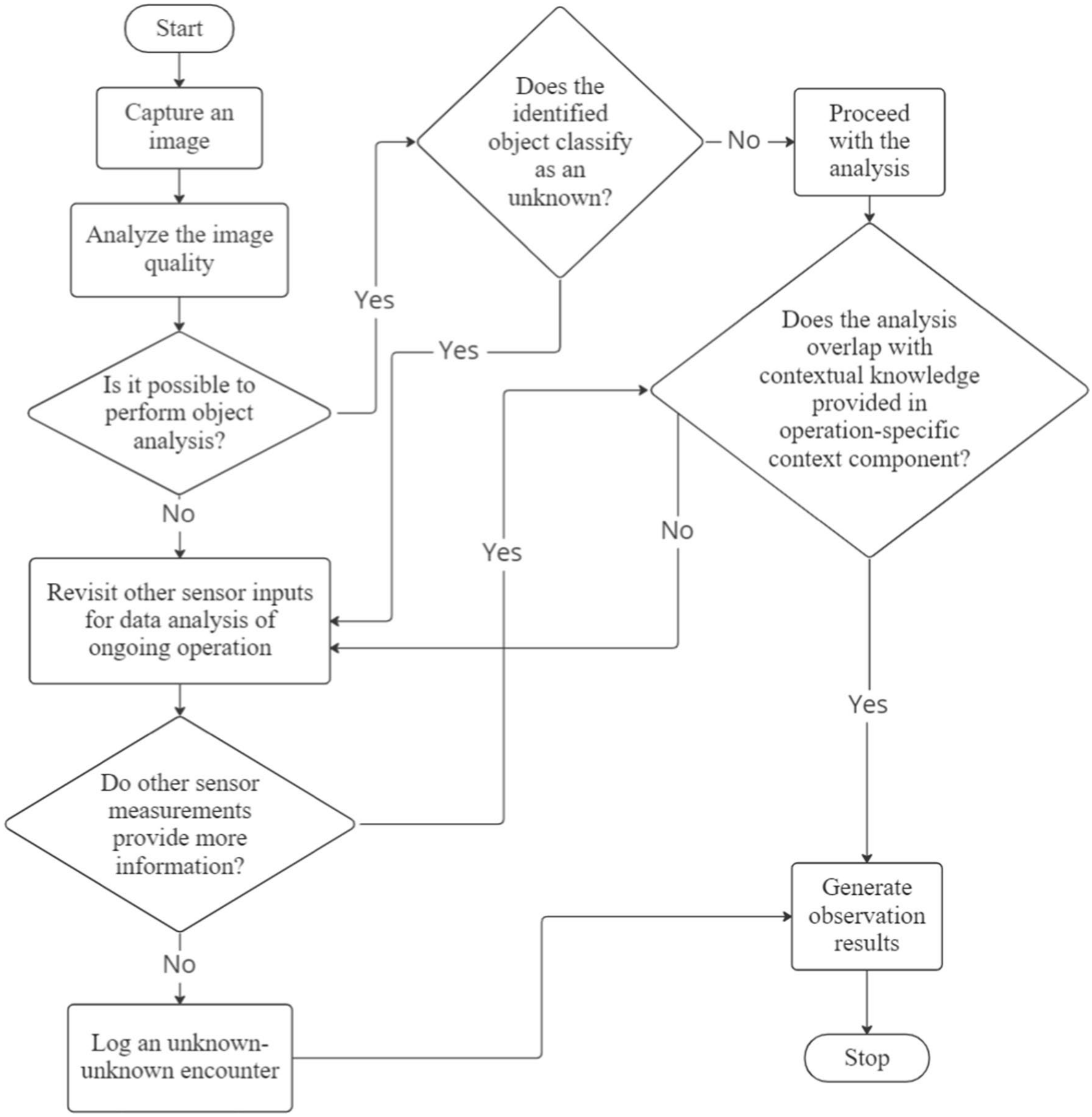

Fig. 6 Image quality analysis flowchart

sensor systems and autonomous drones, has consequentially increased the use of AI methods for data analysis in real-time and near-real-time inspections, primarily with image and video captures. These methods include object classification, anomaly detection, and pattern recognition. Although AI methods may evaluate acquired image data effectively, they have flaws that raise concerns about their reliability, such as bias and an efficiency inclination that wastes resources and misdiagnoses pipeline conditions. In this research paper, we have examined the factors contributing to the enhanced reliability of image-based pipeline material degradation inspection. We proposed context and supervisory components in AI model architecture and rethinking adaptive sensor scheduling, particularly the image-based inspection, by examining the operation-specific context, emerging risks, and patterned expectations.

It is becoming increasingly important to find context in the operations that AI-dependent systems are required to carry out in order to ensure reliable, intelligible, and ethical outcomes. By analyzing a dataset of underwater images captured by an autonomous drone, we intend to further our research on implementing the AI model context component as a part of image-based anomaly detection and object categorization.

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Declarations

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