Survey Article

Autonomous Robotic Inspection for Remote Inspection Technique Systems: A Review

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Abstract: Due to the harsh environment and heavy use that modern marine vessels are subjected to, they are required to undergo periodic inspections to determine their current condition. The use of autonomous remote inspection systems can alleviate some of the dangers and shortcomings associated with manual inspection. While there has been research on the use of robotic platforms, none of the works in the literature evaluates the current state of the art with respect to the specifications of the classification societies, who are the most important stakeholders among the end users. The aim of this paper is to provide an overview of the existing literature and evaluate the works individually in collaboration with classification societies. The papers included in this review are either directly developed for, or have properties potentially transferable to, the marine vessel inspection process. To structure the review, an expertise-engineering separation is proposed based on the contributions of the individual paper. This separation shows which part of the inspection process has received the most attention, as well as where the shortcomings of each approach lay. The findings in this review indicate that while there are promising approaches, according to our metrics there is still a gap between the classification societies' requirements and the state of the art. Our results indicate that, even though there is a lot of quality work in the literature, there is a lack of integrated development activities that achieve a level of completeness sufficient for the classification societies to confidently use them.

Keywords: marine vessel inspection, remote inspection technique, classification society, deep learning, autonomous robots

1. Introduction

One of the most efficient ways of transportation is by sea, which, according to the United Nations Conference on Trade and Development (2019), constitutes over 80% of merchandise trade by volume. It is critical for the environment that marine vessels—especially the large vessels that transport cargo—are safe to operate to minimize the risk of contamination, e.g., oil spills or more abrupt catastrophes such as explosions.

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Figure 1. Example of a drone flying in a ballast tank. If equipped with the right sensory equipment accompanied by a high level of autonomy, the drone can replace human surveyors in the hazardous environments present in the ballast tanks of modern marine vessels.

The International Maritime Organization (IMO) is a specialized agency of the UN and the authority in setting standards for safe shipping. Its main contribution is a universally adopted regulatory framework ensuring that ship owners cannot sacrifice safety for increased market advantages. The level playing field set by the IMO covers all aspects of shipping, including construction and maintenance of marine vessels (International Maritime Organization, 2015).

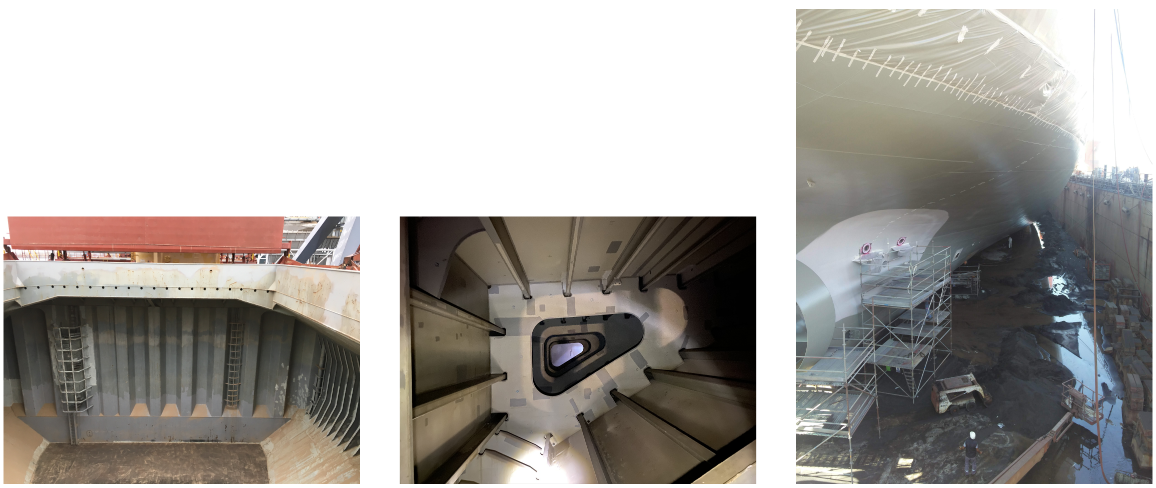
The regulations dictate that cargo vessels have to undergo periodic inspections where, among other tasks, the condition of the vessel is assessed. The main goal of these inspections is to find any defects present on the vessel that may reduce its structural integrity and thus pose a risk of failure during operation. Examples of the most important areas that undergo inspections are shown in Figure 3. The actual inspection is carried out via a collaboration between the vessel owner and a classification society or a class-certified surveyor that enforces the regulations set by IMO. It is up to the individual classification society how they ensure that the regulations set by the IMO are adhered to, and it is thus up to them what technologies and assisting tools they deem suitable for use in the assessment. For this reason, 12 classification societies have formed the nongovernmental International Association of Classification Societies (IACS) (International Association of Classification Societies, 2016), which provides technical support and guidance on the unified regulations set by the IMO. Additionally, they provide support when amendments and changes to the existing regulations occur or new regulations are added.

One of the emerging technologies that classification societies are adopting at an increasing rate is the use of drones (an example of a drone flying in a ballast tank is shown in Figure 1). They serve the purpose of removing human surveyors from the hazardous and unfriendly environments present on a vessel during inspections while still allowing the acquisition of sensory information used in the assessment.

With the recent increased availability of viable drone solutions and the advances in image processing and recognition, the works in the literature trying to automate the inspection process have also increased. The existing literature tends to either focus on detecting defects (Zheng et al., 2002; Ji et al., 2012; Bonnin-Pascual and Ortiz, 2014; Liu et al., 2019), or to provide drones capable of reaching the areas that are difficult to access while balancing the tradeoffs of equipment payload,

(a) **(b)**

Figure 2. Examples of marine vessels (a) during operation and (b) during maintenance in a dock.



(a) **(b)** **(c)**

Figure 3. Examples of areas on a modern marine vessel that have to be inspected: (a) cargo hold, (b) ballast tank (specifically top-side tank), and (c) the outside hull of a vessel.

drone size, operation time, etc. (Ozog and Eustice, 2016; Hover et al., 2012). The IACS has defined some recommendations for how these Remote Inspection Technique Systems (RITS) should operate; however, the general interpretation of it is that any RITS has to be able to represent the same quality of information that a surveyor being physically present would be able to acquire (International Association of Classification Societies, 2016). Thus there are no clear definitions or requirements for the drone, as long as the assessment does not suffer in quality. Thus, a complete/perfect RITS should be capable of delivering the same level of quality inspection as a human surveyor, with all the added benefits of task automation such as easier standardization, repeatability, increased precision, etc. Specifically, the repeatability is of great importance since a vessel (shown in Figure 2) can contain more than 600 000 m^2 of steel, which has to be visually inspected within a 1–2 m observation distance. It is nearly impossible for a human surveyor to maintain focus for the time required to inspect such an amount of steel, resulting in varying and subjective inspections (Ortiz et al., 2016b).

Though it is clear that some progress has been made, it is unclear how close to a complete RITS any single work or collection of works has come, since there exists a general lack of evaluation concerning the regulations as a whole. Thereby, it is hard to quantify how close the community has come to a realistic solution that the classification societies can use.

A previous survey (Bonnin-Pascual and Ortiz, 2019) evaluated the technological advances, particularly within marine vessel inspection. They present defect detection as the detection of cracks and corrosion and robotic platforms suitable for marine vessel inspection. While they provide a comprehensive list of the state of the art, they do not address all of the criteria for a solution to be viable for the classification societies, such as being able to quantify the defects or detecting the type of corrosion.

This paper strives to fill this gap and, in collaboration with a classification society (Lloyd's Register, 2018), evaluate the current status of how close the state of the art is to a fully functioning RITS. This is done by separately investigating a) the expertise and b) the engineering challenges present when capturing information to apply that expertise. Specifically, this paper is interested in identifying the existing works in the literature that encapsulate both the expertise and the engineering as shown in Figure 4. For this paper, expertise is defined as the knowledge and the associated processing ability to assess the condition of a vessel given a selection of sensory information. The engineering aspect concerns the acquisition of the information while raising the autonomy level higher than that of a fully teleoperated drone solution. Thus, engineering encapsulates the physical hardware and control software needed not only to autonomously navigate the relevant inspection areas of the marine vessel but to additionally ensure that the requirements for applying the expertise can be fulfilled with sufficient sensory information.

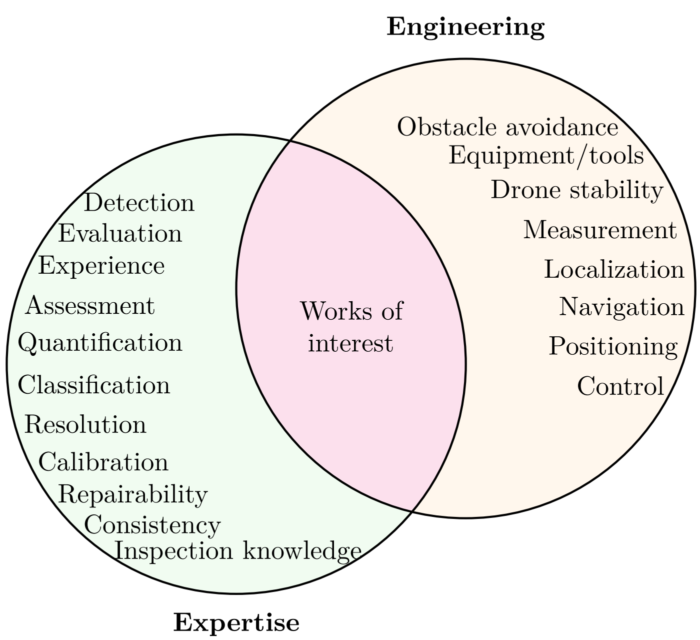


Figure 4. The role of the expert surveyors is to supply their vessel inspection knowledge. However, this knowledge has to be based on sensory information that binds said knowledge to a specific physical context. Thus, any solution attempting to automate a process will have to both capture expertise and gather information. In the context of marine vessel inspection, the knowledge relates to defect detection, classification, and repairability. Engineering relates to supplying the necessary information and navigating the vessel. Thus, in the current work, the literary works of interest are those that tackle the overlap between these two concepts.

In Section 2, the approach employed to evaluate the progress of the state of the art is presented. The metrics defined in Section 2 will be used to score the existing literature within what has been defined as expertise in Section 3 and engineering in Section 4.

2. Metrics definition

The assessment parameters of the marine vessels are derived from the type of materials used for their construction, and they are defined by the classification societies. An example is that the condition of the paint (coating) is assessed to be either good, fair, or poor if there is less than 3%, between 3% and 20%, or more than 20% corrosion, respectively. Similarly, cracks are quantified by their location and physical sizes, such as length and width.

The main job of a surveyor is to document the type of defect, its location, and severity—which in this paper are collectively referred to as expertise since it encapsulates the knowledge and training of the surveyor. Similarly, the engineering aspect is the technology needed to support the expertise. Analogously, for a manual inspection process, this could be the modular scaffolding or the mobile lights required to inspect all areas of the vessel. The following section is a description of how the existing literature is evaluated. The goal of this work is to quantify the development by the community so that it is possible to identify solutions that solve the engineering challenges related to using autonomous drones in confined spaces and/or that try to capture the expertise of human surveyors by evaluating sensory information to assess the condition of marine vessels.

2.1. Expertise

Though there exist defined criteria with regard to the condition of a vessel, few papers in the literature compare against them and, instead, tend to use standard image processing metrics such as confusion matrices and intersection over union. Even though such an approach evaluates the performance of the detection algorithm—and is thus important—it does not reveal whether any progress is being made towards the actual goal of assessing the condition of the vessel in relation to the unified requirements. In this paper, the existing literature is evaluated on six different parameters that represent either parts of the survey used to document the vessel condition or the level of autonomy that the literature is trying to introduce into the assessment process.

Seen from the point of view of the surveyor, some of the tasks related to vessel inspection can be more critical than others. For instance, to the surveyor it may be more important that the autonomous evaluation can detect the type of defect, rather than just being able to determine its location. For this reason, the importance of each evaluation metric is weighted by a classification society (Lloyds Register). The weight ranges from 1 to 4, with 4 being most important and 1 being least important.

The final score of the existing literature will then be given by the following formula:

$$Score = \frac{w_i \cdot v_i}{\sum_i w_i} \tag{1}$$

where w_i denotes the weight given by the classification society, and v_i is the score given for the metric i. The purpose of this evaluation is to quantify the minimum level of expertise captured by any method before it can realistically be considered by the classification societies. The weights given by the classification societies are normalized to be within the same interval as the scoring of the metrics used. For instance, if there is a metric that the classification societies consider essential, but none of the methods score high on this metric, the overall score of the method should be lowered since the presented method would not be of interest to the classification societies. The metrics used are the following, and a definition of the metrics can be found in the related section:

1. Defect detection (Section 2.1.1)
2. Defect location (Section 2.1.3)

Table 1. Examples of how a score is assigned.

Example	**Score**
Defect type	
A work that performs binary classification (i.e., it only concerns the presence of defects/corrosion or otherwise abnormalities).	0.1
A work that actively includes one of the corrosion types stated by the classification society.	0.5
A work that actively includes all of the corrosion types stated by the classification society.	1.0
Defect location	
A work that classifies on a whole image basis without respecting spatial location in any form.	0.0
A work that provides bounding boxes or otherwise proposes some weak form of localization (e.g., through recursive detection) and is strictly bounded to the image plane.	0.5
A work that provides low-level positioning of the defect with respect to some extrinsic reference frame.	1.0
Defect quantification	
A work that does not quantify any detection.	0.0
A work that is able to quantify the detected defects.	0.5
A work that is able to quantify the detected defects such that they can be compared against the existing metrics used by the classification society.	1.0
Autonomous evaluation	
A work that relies heavily on manual operation to function, e.g., a surveyor has to traverse the area with some equipment or remove samples from the vessel to analyze off-site.	0.0
A work that functions to partially automate the evaluation process but still relies on some human interaction, e.g., for result interpretation.	0.5
A work that is able to carry out the entire evaluation process without any prior existing system knowledge.	1.0
Flexibility	
A work that is dedicated to inspecting a single specific element of the marine vessel.	0.0
A work that is dedicated to inspecting parts of a single area of the marine vessel (e.g., parts of the hull).	0.5
A work that is able to be deployed in one, or more, areas of the marine vessel that requires inspection.	1.0

3. Defect quantification (Section 2.1.4)
4. Autonomous evaluation (Section 2.1.5)
5. Flexibility (Section 2.1.6)

To increase reproducibility, Table 1 shows some general examples of what each scoring means.

2.1.1. Defect detection

The ability to detect defects based on sensory inputs is a prerequisite to the works evaluated in this paper. The necessity of this parameter is to sort out approaches that only process or otherwise transform sensory information before any real assessment or evaluation is done. Since this metric is a prerequisite to be considered at all in this evaluation, it has been left out of the final scoring as it only adds a constant bias to all the works evaluated.

2.1.2. Defect type

To identify the severity, the type of defect is important since the maintenance process changes depending on how the vessels' structural integrity is affected. In the standards set by IACS (International Association of Classification Societies, 2016), there are 4 main defect types: cracking, deformation, coating breakdown, and corrosion. It is these types of defects that a surveyor inspecting the structural integrity of a vessel is expected to document and base a final vessel classification on. The underlying relevance of the defect type is determining the likelihood of failure and propagation (e.g., a growing crack), which vary among the four types. Thus, it is fundamental that in order to achieve a complete, or close to complete, autonomous inspection process, any solution or algorithm has to be able to identify the type of defect such that it can be documented in a vessel condition report. Since there are multiple types of defects to be detected, the score has to reflect how many of the necessary defects can be identified. The classification society weighted this as 4, with the reasoning that the type of defect is important to estimate the severity of the defect and thereby the extent of necessary repairs.

2.1.3. Defect location

To efficiently plan any work for maintenance, the location of any defect is required. In this paper, the location of the defect is not necessarily with respect to the vessel itself, but rather just to a fixed frame. The fixed frame can either be the physical location in relation to the vessel or with respect to some other frame such as a sensor frame. Depending on the area of the vessel being inspected, the location can be of higher or lower importance. Generally, the primary structures (e.g., traverse bulkhead, longitudinal bulkhead) are of more importance than secondary structures (e.g., stiffeners, sides, deck, bottom). The surveyor documentation requires that the defects are located with respect to the vessel structure, rather than an arbitrary relative frame (e.g., a camera sensor). This has to be reflected in a score. The weight given to this metric by the classification society is 3, as the location of the defect is important but not critical, since larger areas could be scanned in smaller increments and thereby still reduce the total area requiring subsequent manual inspection.

2.1.4. Defect quantification

A critical part of documenting the condition of the vessel under assessment is to quantify the defects. In some cases, like cracks, this requires physical measurements in terms of length and width, but for other cases the quantification is more ambiguous. One such case is corrosion, which is measured in the percentage of *the area under consideration* (Lloyd's Register, 2018). For visual sensory inputs like imagery, a scale readout is required. If this is not provided, the physical size of the defects is subject to perspective distortions. Similarly, imagery data must be accompanied by some form of image quality indicator along with a calibration procedure that ensures the quality of the sensory information. Similar to defect type, there are multiple ways of quantifying defects, and thus the score has to reflect how many ways any solution or algorithm can quantify defects. With similar reasoning to that for defect location, the metric is given a weight equal to 2. Specifically, the quantification of the defects can in some scenarios be done manually without losing the advantages of an otherwise autonomous solution.

2.1.5. Autonomous evaluation

Some of the proposed solutions in the literature may attempt to only assist the existing manual inspection process. This can, for instance, be achieved by evaluating gathered data offline or by representing it intuitively but still relying on manual inspection. The autonomous evaluation score is thus an encapsulation of how many manual processes are required to be performed for the autonomous inspection. The classification society weighted this metric with a value of 1 since the goal of using autonomous solutions is to remove the human surveyor from hazardous environments. Thus, if the human surveyor is required to be present in the evaluation process, the benefits of performing autonomous evaluations diminish.

2.1.6. Flexibility

Marine vessels contain diverse types of areas that require inspection for defects, ranging from large open spaces such as cargo holds, to small confined spaces like ballast tanks. The need for this metric is to identify the works in the literature that focus on specific areas and those that can perform inspections in multiple areas of the vessel. An example of this distinction is a solution that only works in water on the outside hull of the vessel, and a solution that can be used in cargo holds, vessel hulls, and ballast tanks. Flexibility was given a weight equal to 4 by the classification society with the reasoning that a significant motivation for using a RITS is the ability to reach otherwise hard-to-access areas. Such areas are present all over the vessel, and being able to use the same solution for multiple areas of the vessel is of great importance.

2.2. Engineering

The engineering aspect of performing inspections is the process of acquiring the information required to utilize or apply the expertise. If the inspection is performed on the vessel hull while in water, the engineering aspect is to create a solution that can navigate in water. Since expertise and engineering are separate, this category will also include all those solutions that utilize different forms of drones in a teleoperation setting and still rely on human surveyor expertise for the actual assessment. A pure teleoperated solution still solves many of the challenges present in the current way of performing inspection, such as removing the human surveyor from the hostile environment present in ballast tanks. However, a significant part of the engineering challenge is to be able to traverse the vessel, and since this has to include some form of autonomy, the engineering score used to evaluate the existing literature is derived by the Society of Automotive Engineers (SAE) (SAE International, 2021). This adaption consists of six steps with increasingly higher requirements for the level of automation. Note that this is a sequential score, i.e., it is not possible to attain level 3 without having attained level 2, etc.:

1. No Automation (Section 2.2.1)
2. Assistance Automation (Section 2.2.2)
3. Partial Automation (Section 2.2.3)
4. Conditional Automation (Section 2.2.4)
5. High Automation (Section 2.2.5)
6. Full Automation (Section 2.2.6)

2.2.1. No Automation

Any drone that is fully controlled by the operator at any given time with only very basic functionalities is considered a nonautonomous drone. Either the operator of the drone must be physically present in the same area the drone is flying in, or a live video feed from the drone has to be transmitted to them. It is at this level of automation that most consumer drones reside.

2.2.2. Assistance Automation

Assisted drones can traverse simple environments controlled by the operator while providing a pose estimate for the operator. A complete description of the environment is available to the drone, and any actions the drone has to perform are executed by the operator. Similarly, it is up to the operator to decide which actions/tasks must be performed. Thus the most significant advancement of the works at this autonomy level is that the drone is capable of estimating its position.

2.2.3. Partial Automation

A partially automated drone maintains its ability to return pose estimates within the environment and gains the skill to map the environment while moving around. The operator still has to manually move the drone to the inspection area, but the drone can generate and follow a local inspection trajectory under the supervision of the operator.

2.2.4. Conditional Automation

At this automation level, the drone possesses the ability to observe and adapt trajectories as it traverses the environment. The interference of an operator is limited to specifying the type of environment, and it only interrupts in rare situations. The main milestone is the capability to plan local actions such as trajectories to solve a task, and the drone being capable of adapting to a changing and somewhat dynamic environment. In theory, therefore, it is no longer required for the operator to maintain focus on a single drone, as the automation level is high enough for both traversing the environment and adapting to changes in the environment.

2.2.5. High Automation

Employing highly automated drones, the role of the operator is shifted from using the drone as a tool to managing the information gained from the task the drone is solving. Thus, the drone no longer requires monitoring, and it can initiate new tasks required by the operator. The drone itself will determine when, where, and what has to be done. At this level, the drone is capable of giving a consistent stream of information related to inspections of the vessel from which a continuous estimation of the condition can be made. It is up to the drone to ensure that the dynamic environment is explored, and, based on sensory information, that it can solve the task it was given at launch. At this level, it is still required for the operator to initiate the drone to begin execution.

2.2.6. Full Automation

In the full automation category, the drone learns from past experiences to improve the execution efficiency of the task. The drone is able to perform under any conditions in which an operator would normally operate.

3. Assessment of the Literature with regard to Expertise

The premise of being able to apply expert knowledge is the presence of information that can be interpreted. This information can come from a wide variety of sources, such as visual images, nonvisual images, ultrasonic measurements, or even statistical methods used to describe areas at risk as a function of vessel age, type, previous assessment, etc. The process of applying expertise to this information can be manual, semiautomatic, or automatic. Applying the expertise manually involves human surveyors assessing the sensory information and, based on their experience, classifying the condition. Similarly, semiautomatic solutions can consist of tools that automate parts of the inspection process, such as easing the documentation process or by only fulfilling some of the defect metrics described in Section 3.

It is not only within marine vessel inspection that attempts have been made to automate the inspection process by capturing the expertise in the form of sensory input followed by an artificial assessment. Such examples can be found in railways (Hodge et al., 2015), bridge structures (Jahanshahi et al., 2009), wind turbine blades (Eich and Vögele, 2011), and tunnels (Balaguer et al., 2014). Earlier surveys on inspection also date far back in time (Newman, 1995). Thus, there exists a wide interest in automating the inspection processes, and since the elements used in many large construction efforts consist of roughly the same materials, e.g., steel and concrete, a solution not directly intended for marine vessel inspection may include the same components required for this application, too.

For this paper, however, we are focused only on existing literature work directly related to marine vessel inspection due to it being unfeasible to test all existing works on inspection processes on marine vessels. As with many inspection processes, the inspection of marine vessels currently relies on visual inputs from the human surveyor, and thus many attempts at automating the inspection process use visual cameras. The following section reviews the attempts to assess the condition of marine vessels by categorizing them into spatial-domain, wavelet, histogram, and deep learning methods. Finally, for the sake of completeness, a subsection is reserved to present the works that attempt to evaluate the corrosion using nonvisual methods.

3.1. Spatial-domain-based methods

Not only has corrosion been detected with image processing, but cracks and other types of deformations have received attention as well. Zheng et al. (2002) used a camera to capture information of a sample of metal, which is then analyzed using a combination of thresholding and morphology. The parameters for the morphology process are learned through a genetic algorithm. The main disadvantage of this method is the requirement to obtain a sample of the metal to be inspected. This makes it infeasible for large-scale vessel inspection.

Segmentation of corrosion in images is a task that desirably gives an exact location of the corrosion in the image. One of the ways to segment an image is to perform a watershed transform (Vincent et al., 1991). One of the great challenges when performing a watershed transform for corrosion detection is segmentation, specifically when the image contains noise. Ji et al. (2012) presented an improved watershed transform where the incorporation of the value and brightness of each pixel together with the canny operator was proposed (Canny, 1986). The result was a more robust segmentation and less sensitivity to noise in the image. Canny edge detection has also been used directly for segmentation (Zaidan et al., 2010).

Saliency has been utilized on multiple occasions by Bonnin-Pascual and Ortiz (2014, 2016a,b, 2018, 2017). The saliency map consists of a topographic map where bright values represent areas with defects and lower values represent areas with no defects. Bonnin-Pascual and Ortiz (2018) used a saliency map as an input to two kinds of detectors: contrast-based and symmetry-based. The two types of detectors are also combined to produce a single defect detector in three different ways using the logical operators **OR**, **AND**, and a custom or operator that averages the contribution of the contrast channels, intensity, color, and orientation as well as the symmetry map. One of the main results of this work is that their final defect detector is able to produce an Area Under the Curve [AUC, Fawcett (2006)] value of 0.8. Additionally, it was found that a contrast-based detector performs better than a symmetry-based detector, suggesting that contrast is capable of capturing more information used to discriminate between defective areas and nondefective areas.

Maglietta et al. (2018) explored an ensemble of different classifiers ranging from a support vector machine and Fisher Discriminant Analysis to K-nearest neighbor. The features used for the classifiers are all computed from the Hue, Saturation, and Value (HSV) color space. The main contribution is a combination of all the classifiers trained individually on the training features. Then, the final classifier, named PICARD, classifies inputs based on a majority vote of all six classifiers. Similarly, Bonnin-Pascual and Ortiz (2011) used AdaBoost consisting of a linear combination of weak classifiers implemented using 48 Law's texture energy filters. 25 images were used to generate 39 746 patches, of which 12 952 were labeled defective. 50% of the total amount of patches were used for training. One of the main results is a false positive and false negative of 17.16% and 3.39%, respectively, with the reasoning that it is more important to detect all defects than to have false positives. Eich et al. (2014) obtained a global classifier by chaining two smaller classifiers together. The first classifier relies on the fact that corroded areas in images have a rough texture measured by the energy of the symmetric gray-level co-occurrence matrix. Based on the energy field, a threshold determines candidates for corrosion. The second classifier uses the output of the first classifier and the fact that corroded areas are bounded to the hue-saturation plane. Subsequently, a bidirectional histogram is built, on which a filter is used to zero out entries that are 10% below the peak. After applying a Gaussian filter, the remaining pixels are thresholded based on the filtered histogram.

Ortiz et al. (2016b,a) explored a combination of traditional image-processing techniques and neural networks. Initially, they use a set of selected features in the image that is classified using a three-layer neural network with the goal of segmenting any corrosion defects in the image. The features are computed using a modified version of a hierarchical tree-structured color palette (Orchard and Bouman, 1991), and the dominant colors of a small patch of the original image are extracted and then fed into the neural network. A second experiment used k-means (Theodoridis and Koutroumbas, 1999) initialized by K-means++ (Arthur and Vassilvitskii, 2007) to avoid clustering the k-means in the same area in the color space. Lastly, Ojala et al. (1996) presented an experiment where texture analysis is used to extract features and perform local binary patterns to weigh the difference in pixel intensities in the image. One of the main downsides of the different feature extractors used by Ortiz et al. (2016b,a) is the required time to compute the features since they all operate on patches of the image, and the classification depends on the size and number of defects present in the image.

3.2. Wavelet-based methods

Some of the early work on applying image processing tools on images of corrosion was performed by Siegel et al. (1988) and Siegel and Gunatilake (1998), who used a discrete wavelet transform. Initially, a three-level wavelet decomposition on an image is applied, after which the image is divided into patches with a stride equal to the patch size. A feature vector of each patch is extracted consisting of the energy response of the wavelet transform at each frame. Finally, the classification of the feature vectors was performed by a 3-layer feed-forward neural network trained in a supervised setting. Though the application is corrosion on aircraft skin, it is included here for completeness since it uses the wavelet transform for corrosion detection, thus making it directly related to the application of marine vessel inspection considered in this paper.

Another example of the use of the wavelet transform was presented by Fernández-Isla et al. (2013), where corrosion located on the vessel hull was detected. The decomposition used in their work consists of applying all combinations of low- and high-pass filters and thereby obtaining four subimages from the one original image on which the process was repeated recursively. The image with two low-pass filters applied is also referred to as the image approximation, as it is just a smoothened version of the original image. The main contribution of that work is that the decomposition level is determined by computing the ratio between the Shannon entropy of the image approximation and the sum of the entropy of the other subimages.

3.3. Histogram methods

Navarro et al. (2010, 2013) utilize a histogram of the image to determine the background based on the principle that the majority of images will be without corrosion or other defects, and thus they will be similar in color (due to the coating). The image is then thresholded based on the histogram to segment the defects.

Digital images are usually represented in the RGB color space; however, multiple other color representation models exist, some of which contain desirable properties for the classification of objects that are characterized by specific color (Busin et al., 2009). Choi and Kim (2005) interpreted images in the Hue, Saturation, and Intensity (HSI) color space from which they build histograms of patches of the image with a size of 10×10 pixels. The histograms for each channel are treated as random variables on which they apply principal component analysis and varimax. The output of this process is features used for classification. Their work concludes that the mean H, median S, skew of S, and skew of I together with some physical characteristics such as the area, perimeter, length, and mean radius can be used to obtain a classification accuracy of approximately 85%.

Aijazi et al. (2016) used a more comprehensive approach where external RGBD scanners are placed around the vessel when in drydock to create a 3D representation of the vessel including the color. Defects are then classified by considering a small area of the vessel surface and generating a histogram after the color channels have been converted to the HSV color space. Depending on the size of the area that is corroded, segmentation happens based on either a histogram or a threshold.

3.4. Deep learning methods

3.4.1. Classification

Petricca et al. (2016) used pure deep learning classification for binary classification of corrosion on a whole-image level. It can only be used to detect the presence of corrosion, not where it is located. Though the training dataset size was very small, the method still managed to achieve an accuracy of 89.1%.

3.4.2. Object detection

More recent deep learning architectures have also been used for defect detection. Some preliminary results were presented by Ortiz et al. (2018), where the authors have used transfer learning on a Single-Shot multibox Detector (SSD, Liu et al. (2016)) and a Faster R-CNN (Ren et al., 2017) with a VGG network (Simonyan and Zisserman, 2014) as a backbone. Instead of using the common intersection over union metric, an intersection of prediction was employed with the reasoning that detecting the presence of defects is more valuable than generating a bounding box that tightly fits the ground truth. The findings indicate that Faster R-CNN is better suited for corrosion detection than the single shot multibox detector.

Deep learning architectures have also been used by Liu et al. (2018c), and their work has continued (Liu et al., 2018a,b). In the former, transfer learning was used to train a Faster R-CNN architecture with a VGG19 backbone, and the system was able to detect three types of defects: surface-based corrosion and coating breakdown, edge-based corrosion and coating breakdown, and noncoating failure. In general, the work outlined by Liu et al. (2018c,a,b) presents a complete system including a drone and user interface for image processing and evaluation as well as the option for generating a report of the results. The main results of using Faster R-CNN with a VGG19 backbone is an accuracy of 81.37% when separating corrosion on welds and edges, and 89.54% otherwise, which indicates deep learning approaches may be suitable for vessel classification. The same authors have tried to improve the accuracy of the system by introducing active human intervention (Liu et al., 2019). The human intervention is a human surveyor manually assessing an image that has been preprocessed by adjusting the brightness, gamma correction, and histogram equalization.

General-purpose deep learning architectures are not the only ones that have been explored to detect corrosion. Bastian et al. (2019) proposed a custom deep neural network to classify the level of corrosion on pipes as either None, Low, Medium, or High. To localize the corrosion within the image, the authors proposed to recursively subsample the input image if it contains medium or high levels of corrosion until the image size reaches a lower threshold. Consequently, this also means that the number of inference calls on the classification network is high.

3.4.3. Segmentation

Some of the most popular deep neural networks have been investigated by Andersen et al. (2020) to identify the best suitable pipeline to perform inspections on robotic platforms with limited computational power. Specifically, two pipelines were proposed: The first one included a simple network performing binary classification on the image level, and, if defects were detected, a larger network performing pixel-wise localization was deployed. Based on the results from that network, the image would be classified as *good, fair*, or *poor*. Similarly, the second approach was to simply use a smaller network to categorize the image as *good, fair, poor* directly and only use a larger image network for localization. Based on their findings, the best performing pipeline is the one that performs binary classification and overall category conditioning with a large pixel-wise segmentation. Additionally, among the investigated architectures, the Mask-RCNN performed the best, indicating that larger networks may be a necessity for high-quality inspection results.

One of the biggest challenges when employing deep learning approaches is the large number of annotated images required for creating a robust model. For this reason, there exist multiple ways to annotate an image, some of which were explored by Yao et al. (2021). Specifically, a loss function based on the centroid loss was proposed that seeks to minimize the effect of weak annotations on the network architecture (Attention U-Net) (Oktay et al., 2018). They conclude that their approach to employing weakly supervised training produces similar results at a reduced annotation burden when compared to traditional full supervision in the task of corrosion detection in images from marine vessels.

3.5. Nonvisual methods

In this section, methods that do not directly rely on imagery are presented. The purpose is to include methods that use other sensory equipment than those naturally available to a human surveyor. The methods include using the grid method, ultrasonic, and augmented reality. The former is presented by Avril et al. (2004) and is an approach to detect cracks by applying a grid pattern on the inspection surface, which in the specific experiments is a transparent sheet transferred to the inspection specimen. By analyzing the phase modulation of the light caused by the crack with Windowed Fast Fourier Transform, it is possible to separate the discontinuities in the phase with a simple threshold. Cracks as small as 5 μm in width are successfully detected, and their location is determined with an accuracy of 1.2 mm. While the detection and localization accuracy are more than sufficient for the inspection of marine vessels, it has to be noted that this method relies heavily on a fully controlled environment.

Other methods utilize ultrasonic measurements to measure the thickness of the steel. The advantage of this approach is an exact measurement of the integrity of the steel from which the vessel is made. Akinfiev et al. (2008) presented a robotic solution fitted with an ultrasonic sensor. Though the sensor was mounted on a robotic platform, the only expertise in relation to the condition of the vessel was provided by a human surveyor.

The use of augmented reality has also been explored for inspection (Dini and Mura, 2015). Some of the applications highlighted by Dini and Mura are related to inspection by indicating faults and defects to the operator. The operator can also use augmented reality to point out faults and defects manually, and then save the location of the defect automatically. Papachristos and Alexis (2016) included augmented reality by utilizing a drone equipped with a live camera from which the operator is then shown the live feed.

More statistical approaches exist that rely on the physical process of corrosion. Gardiner and Melchers (2003) identify a set of parameters divided into operational and internal parameters. One of the operational parameters is the ballast ratio—the ratio between how long the vessel is loaded with cargo and the age of the vessel. Other parameters are trade route, coal corrosivity, and frequency of cargo changes. Thus, the operational parameters consist of the external forces applied to the vessel that influences its condition. On the contrary, the internal parameters describe the internal design measures taken to prevent corrosion. These include corrosion protection systems and structural member location and orientation. The conclusion of the work was a proposal to monitor the aforementioned parameters to build a corrosion rate database that would enhance the reliability of corrosion prediction models.

One of the most effective measures of preventing corrosion in marine vessels is by applying paint on the steel surface, which prevents direct contact between the salt water and the steel. The disadvantage of coatings is the difficulty in detecting corrosion underneath them. Therefore, Qaddoumi et al. (1997) proposed the use of microwave sensors to detect corrosion under paint and composite laminates. Their experimental setup included a painted steel plate on which they were able to detect corrosion even with varying paint thickness.

3.6. Summary

Table 2 shows the main reported results for each evaluated paper. Note that these results are reported directly from the papers without scrutiny. Thus, a comparison is meaningless without referencing the underlying methods. It is included here for completeness as it gives an overview of what method the different papers have used to evaluate their results and how they have performed.

The scoring based on the weighting from the classification society and the scoring of the metrics for each work considered in this paper is listed in Table 3. It should be noted that while all of the works have some relation to the marine vessel inspection process, some of the presented works also include more general applications, such as crack detection on concrete structures and/or spalling.

From Table 3 it is clear that methods that rely on some form of deep neural network score better on the metrics used in this paper. Specifically, they can distinguish between more types of defects, alleviating the subjective assessment of the surveyor. Generally, all the methods investigated in this paper score poorly in quantification, i.e., they do not incorporate a way of quantifying the defects. Most of the methods use some form of in-image localization. This approach has the advantage of only requiring a single image, however it limits the quantification to be strictly on the image plane. Since the area affected by a defect will be perceived drastically differently depending on the perspective and viewing angle, it is difficult to get a real-world quantification of the defects. One of the advantages of using camera images is the high level of automation that can be achieved as well as the flexibility. Cameras can be small in size so as to fit in even tighter places while only requiring a light source when there is no natural light present, such as when inspecting a cargo hold or a vessel hull.

Table 2. Reported results for each evaluated paper. Note that the results reported here are taken directly from the respective papers. Thus a direct comparison between the results is of little value without also considering the underlying methods and metrics.

	Evaluation method	**Results**
Siegel et al. (1988)	Visual evaluation	Demonstration
Qaddoumi et al. (1997)	Visual evaluation	Demonstration
Siegel and Gunatilake (1998)	Visual evaluation	Demonstration
Zheng et al. (2002)	Hole and crack detection Accuracy on dataset	holes 91% cracks 86%
Gardiner and Melchers (2003)	Parameters affecting corrosion	Degradation hierarchy
Avril et al. (2004)	Metric size of cracks	smallest detection 5 μm
Choi and Kim (2005)	Accuracy on dataset	corrosion 85%
Akinfiev et al. (2008)	Not stated	Not stated
Zaidan et al. (2010)	Visual evaluation	Demonstration
Navarro et al. (2010)	Classification rate	92.5%
Bonnin-Pascual and Ortiz (2011)	Confusion matrix	FP=20.47 rate, FN=20.91 rate, FP=17.16%, FN=3.39%
Ji et al. (2012)	Not stated	Not stated
Jahanshahi et al. (2011)	Metric size of cracks	Maximum deviance from ground truth <15 mm
Navarro et al. (2013)	Accuracy on dataset	95%
Fernández-Isla et al. (2013)	Confusion matrix	FP=6.8 error, FN=0.9 error
Eich et al. (2014)	Confusion matrix	Corrosion: FP=9.8%, FN=5.86% Crack: FP=0.72%, FN=0.52%
Bonnin-Pascual and Ortiz (2014)	AUC	0.9
Dini and Mura (2015)	Not stated (augmented reality)	Not stated
Papachristos and Alexis (2016)	Not stated (teleoperation)	Not stated
Bonnin-Pascual and Ortiz (2016b)	AUC	0.8
Bonnin-Pascual and Ortiz (2016a)	AUC	0.9
Ozog and Eustice (2016)	Not stated	Not stated
Petricca et al. (2016)	Confusion matrix	Accuracy=92%
Aijazi et al. (2016)	F1 measure	0.90
Ortiz et al. (2016a)	Success rate	0.87
Ortiz et al. (2016b)	F1 measure	0.92
Ortiz et al. (2017)	Visual evaluation	Demonstration
Yang et al. (2018)	F1 measure	Accuracy=97.96 Precision=81.73 Recall=78.97 F1=79.95
Maglietta et al. (2018)	Accuracy on dataset	Corrosion 0.961
Ortiz et al. (2018)	Intersection over Precision	Visually inspected on graph
Bonnin-Pascual and Ortiz (2018)	AUC	Visually inspected on graph
Liu et al. (2018c)	Confusion matrix	Accuracy=81.37% on 5 classes
Liu et al. (2018a)	Confusion matrix	Accuracy=89.54% on 5 classes
Liu et al. (2018b)	Confusion matrix	Accuracy=89.54% on 5 classes
Bastian et al. (2019)	Accuracy and F1	Accuracy=98.2, F1=96.73
Liu et al. (2019)	Confusion matrix	Accuracy=89.54% on 5 classes
Hoskere et al. (2020)	Accuracy on dataset	91.7%
Andersen et al. (2020)	Intersection over Union	0.156
Yao et al. (2021)	Intersection over Union	0.7542

Table 3. The score of all references. The metrics are used to compute the final expertise score according to Eq. (1). The expertise scoring lies in the interval [0 − 1] with a higher value meaning a better fit between the expectations of the classification societies and the actual level of expertise captured.

	Method	Type	Location	Quantification	Autonomous evaluation	Flexibility	Expertise score
Andersen et al. (2020)	DL	1.0	0.9	0.3	0.5	0.9	0.814
Liu et al. (2018b)	DL	0.9	0.8	0.3	1.0	0.9	0.800
Hoskere et al. (2020)		0.9	0.8	0.3	0.9	0.9	0.793
Liu et al. (2018a)	DL	0.8	0.8	0.3	1.0	0.9	0.771
Liu et al. (2019)	DL	0.8	0.8	0.3	1.0	0.9	0.771
Jahanshahi et al. (2011)		0.5	0.8	1.0	0.5	0.9	0.750
Bonnin-Pascual and Ortiz (2014)	Spatial	0.8	0.5	0.1	0.9	0.9	0.671
Ortiz et al. (2017)		0.8	0.5	0.1	0.9	0.9	0.671
Liu et al. (2018c)	DL	0.9	0.5	0.1	0.5	0.9	0.671
Yang et al. (2018)		0.5	0.5	0.5	0.9	0.9	0.643
Yao et al. (2021)		0.6	0.5	0.3	1.0	0.7	0.593
Fernández-Isla et al. (2013)	Wavelet	0.5	0.5	0.1	0.9	0.9	0.586
Bonnin-Pascual and Ortiz (2016b)	Spatial	0.6	0.3	0.1	1.0	0.9	0.579
Bonnin-Pascual and Ortiz (2016a)	Spatial	0.6	0.3	0.1	1.0	0.9	0.579
Bonnin-Pascual and Ortiz (2018)	Spatial	0.6	0.3	0.1	1.0	0.9	0.579
Bonnin-Pascual and Ortiz (2011)	Spatial	0.5	0.5	0.0	0.9	0.9	0.571
Eich et al. (2014)		0.6	0.3	0.1	0.9	0.9	0.571
Ozog and Eustice (2016)		0.1	1.0	0.8	1.0	0.5	0.571
Bastian et al. (2019)		0.5	0.7	0.6	0.5	0.5	0.557
Ortiz et al. (2016a)	Spatial	0.5	0.5	0.1	0.5	0.9	0.557
Ortiz et al. (2016b)	Spatial	0.5	0.5	0.1	0.5	0.9	0.557
Akinfiev et al. (2008)		0.5	0.5	1.0	0.8	0.3	0.536
Ortiz et al. (2018)	DL	0.5	0.3	0.1	0.5	0.9	0.514
Choi and Kim (2005)	Histogram	0.5	0.1	0.1	0.9	0.9	0.500
Aijazi et al. (2016)	Histogram	0.5	0.9	0.9	0.5	0.0	0.500
Navarro et al. (2010)	Histogram	0.5	0.5	0.3	0.8	0.4	0.464
Navarro et al. (2013)	Histogram	0.5	0.5	0.3	0.8	0.4	0.464
Petricca et al. (2016)	DL	0.5	0.0	0.0	0.5	0.9	0.436
Avril et al. (2004)	Nonvisual	0.5	0.5	1.0	0.1	0.0	0.400
Ji et al. (2012)	Spatial	0.4	0.5	0.8	0.5	0.1	0.400
Zaidan et al. (2010)	Spatial	0.5	0.3	0.0	0.5	0.5	0.386
Siegel et al. (1988)	Wavelet	0.5	0.8	0.1	0.1	0.1	0.364
Siegel and Gunatilake (1998)	Wavelet	0.6	0.5	0.1	0.5	0.1	0.357
Papachristos and Alexis (2016)	Nonvisual	0.0	0.8	0.1	0.1	0.5	0.336
Dini and Mura (2015)	Nonvisual	0.0	0.8	0.1	0.0	0.5	0.329
Maglietta et al. (2018)	Spatial	0.5	0.5	0.3	0.5	0.0	0.329
Zheng et al. (2002)	Spatial	0.5	0.5	0.0	0.1	0.0	0.257
Qaddoumi et al. (1997)	Nonvisual	0.5	0.3	0.1	0.0	0.0	0.221
Gardiner and Melchers (2003)	Nonvisual	0.5	0.0	0.5	0.0	0.0	0.214

Another conclusion from the table is that the differentiation between defect types has been neglected. A common trend has been to find corrosion or cracks, with none of the investigated methods addressing the need for also detecting deformations in the steel of the vessel. These types of damage are not infrequent and can occur when the anchor hits the hull of the vessel or when loading/unloading cargo. Some of the more severe deformations can occur when a vessel is sailing in low depths or due to collisions—the latter accounting for 35% of marine vessel accidents (Lim and Lee, 2018).

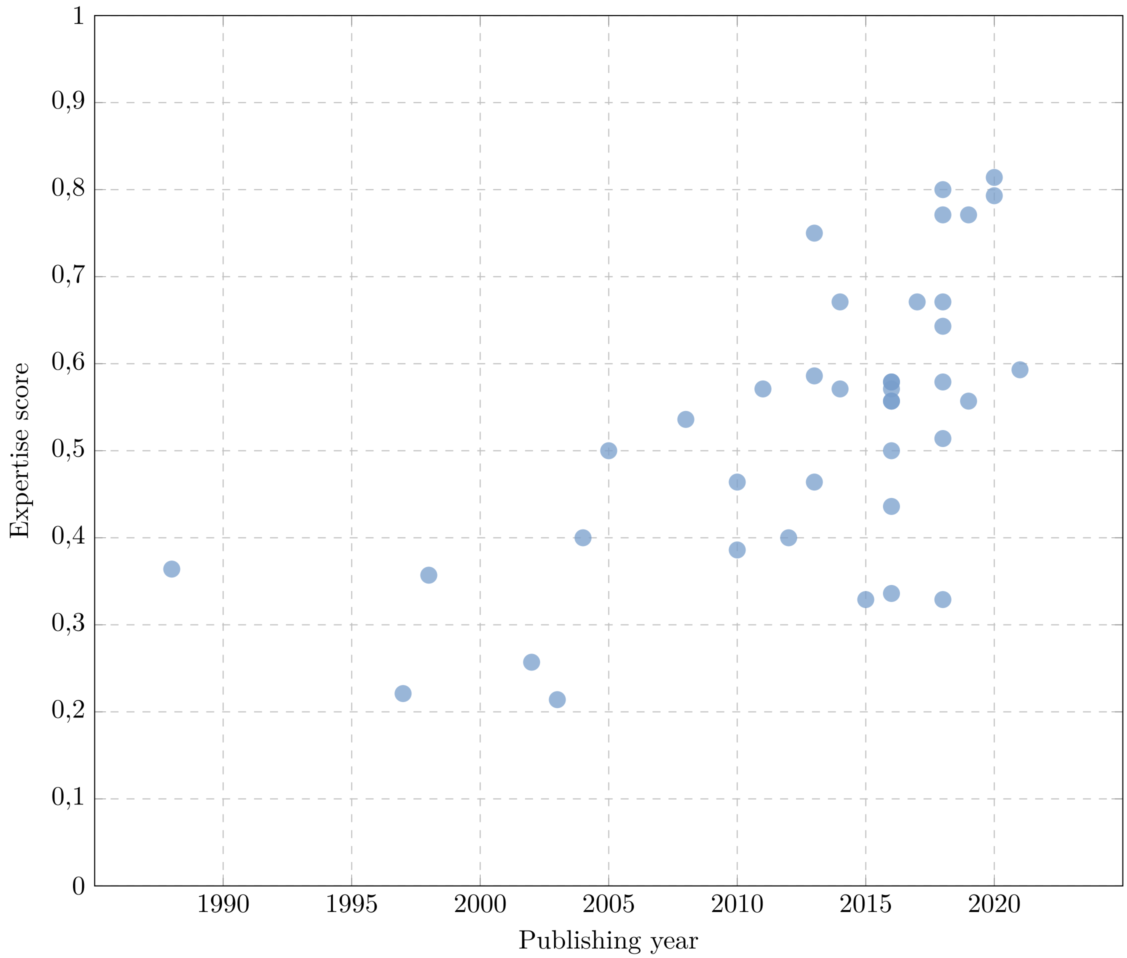


Figure 5. The attention the marine vessel inspection process has received over the last 35 years from an automation perspective has been increasing. This is an indication of the technological advancement that has been made within image processing and computer vision, as that is by far the most popular approach to automating marine vessel inspections.

The attention the marine vessel inspection process has received over the last 35 years—from an automation perspective—has been increasing steadily, as indicated by Figure 5. The number of publications shows an increasing interest in the topic, and with the recent advances in deep learning and computer vision, the level of expertise that can be reproduced autonomously is steadily rising according to the metrics defined in this paper.

To achieve a higher expertise score, it is clear there has to be a bigger focus on quantifying any detected defect. Detecting different kinds of defects has been addressed in some cases with the use of deep learning that is capable of distinguishing multiple types of defects, and in some cases providing an in-image segmentation of the defect. While this provides some form of location, it is not directly possible to transform a single image coordinate into a usable 3D coordinate that can be used by repairmen to localize the defect. As technology advances, the range of sensors capable of capturing 3D information increases. A simple solution to the localization problem would simply be to use a stereo camera setup that can provide a simple form of 3D localization (Brogaard et al., 2021a). The disadvantage of stereo vision is possibly the difficulty in achieving high enough accuracy to also perform quantification. Andersen et al. (2021a,b) showed how quantifying the amount of corrosion can be done on a higher level; however, the severity of both deformations and cracks has to be quantified using physical distance units. This might require a higher level of detail than a stereo vision camera setup can provide. Unless an orthophoto can be produced, a better approach might be to use a laser range sensor that is capable of producing high-accuracy point clouds.

4. Evaluation with regard to the Engineering Aspect

Autonomous robotic platforms for vessel inspection are still in their early stages, and few systems provide a high level of mobile autonomy. This section will cover the level of autonomy that is currently available using a taxonomy inspired by the SAE taxonomy (SAE International, 2021) (see Figure 6). The SAE taxonomy was originally intended for motor vehicles on the roadway system; however, the same reasoning can be applied to any autonomous vehicle. Thus, the gradual removal of the operator is similar for both grounded vehicles and aerial vehicles, ultimately progressing to full autonomy without the influence of an operator (Lee et al., 2021). In the context of drone applications in confined spaces, the specific adaptation used here is described in Section 2.2. For each level of autonomy, the relevant literature will be reviewed and categorized by the relevant taxonomy of automation. The levels do not implicitly describe the robustness of each system. Two systems in the same category can perform differently with regards to—for example—accuracy, precision, and how they handle disturbances. Likewise, the levels will not differentiate whether the drone is airborne, subsea, or ground-based.

Drones/robotic platforms that are not aimed at vessel inspections, but can provide a comparably high level of autonomy, will also be reviewed for the purpose of determining a future outlook on what research could be applied to conduct autonomous vessel inspections.

4.1. SAE 0—No Automation

The first category, where the human is in control of all parts of the navigation during the vessel inspection, primarily consists of legged and so-called crawler platforms operating above the sea surface. Small 4-legged robots are presented by Bandyopadhyay et al. (2018), where magnets are attached to each foot to ensure the capability of climbing vertical surfaces. Furthermore, the authors enhanced its capability to climb on industrial beams with a thickness of less than 5 cm, and through

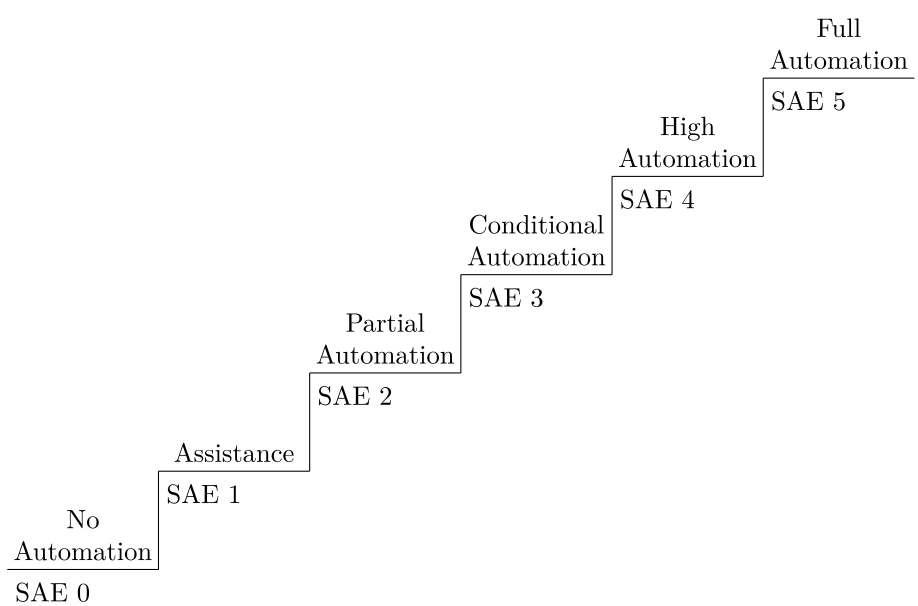


Figure 6. The autonomy taxonomy used here is sequential, starting at no automation and progressively decreasing the involvement of the operator to the point of a self-sustainable solution with full automation.

narrow gaps of 23 cm. Other approaches use magnetic wheels (Caccia et al., 2010; Eich and Vögele, 2011; Eich et al., 2014) or chainlike tracks with inserted magnets in each link (Huang et al., 2017). Alkalla et al. (2015b,a) have investigated the possibility of a rubber-wheeled robot with top-mounted propellers to provide a thrust that increases the friction between the wheels and the surface. The hybrid actuation approach adds the advantage of climbing over vertical walls made of nonmagnetic materials, such as glass fiber, wood, and aluminum. Garcia-Fidalgo et al. (2015) used a manually controlled Unmanned Aerial Vehicle (UAV) to collect image data of a wall from a cargo hull of a container vessel. These images were then offloaded from the drone and used to build a mosaic of the wall, with the benefit of an increased overview of the inspection area.

None of the aforementioned research efforts in this category can be used to aid in autonomously inspecting the vessel.

4.2. SAE 1—Assistance

Within this level of autonomy, the operator enjoys some level of assistance in controlling the robotic platform, which could be in the form of localization and/or a stabilization system. Examples of localization systems are the relative pose estimations for subsea hull inspection presented by Schattschneider et al. (2011) and Chung and Kim (2018). Chung and Kim (2018) and Negahdaripour and Firoozfam (2006) use stereo vision to get a relative pose by matching image feature points between the camera views and frames. Both systems are tested on a real vessel; Chung and Kim (2018) tested their system on a 19×2 m hull section of a real marine vessel. The system was verified by showcasing the reconstruction of the hull section using the pose and images along the inspection path. Another approach by Ozog and Eustice (2016) uses the CAD model of the hull in combination with a camera and a Doppler velocity log (DVL) to localize itself with respect to the coordinate frame of the hull. By also adopting a bundle adjustment system, the authors built a mosaic map overlayed on the CAD model of the hull.

Absolute localization systems for UAVs operating in the confined spaces of the vessel were recently investigated (Brogaard et al., 2020, 2021b,c). A combination of Visual Inertial Odometry (VIO) and detection of existing known structural 3D landmarks was used by Brogaard et al. (2020) to estimate the absolute pose in a mockup model of a water ballast tank. This had the advantage of only requiring a high-level map of the environment. Brogaard et al. (2021b,c) used deep neural networks to generate accurate 3D feature descriptors within an existing point cloud map and for the current viewpoint of the vehicle. The feature descriptors were then matched and used together with a visual-inertial odometry estimate in an extended Kalman filter, resulting in an absolute pose estimate.

A magnetic track/belt robot was proposed by Milella et al. (2017), which uses computer vision to localize the robot and create a mosaic map of the traveled trajectory. The system was tested in the cargo hulls of a bulk carrier, and according to the experiments it was able to combine images and create a 2D overview map of approximately 1×3 m of a section of the wall of the cargo hull. Similarly, Menegaldo et al. (2008) developed a magnetic track/belt robot capable of performing thickness measurements on the dry parts of a hull on a marine vessel. The robot was able to maintain an estimation of its position using an extended Kalman filter to fuse wheel encoder readings and IMU data.

4.3. SAE 2—Partial Automation

Most subsea inspection systems are naturally focused on the outer hull of the vessel. Ozog et al. (2017, 2016) and Kim and Eustice (2009) focus on hull mapping with simple path-planning systems built into the commercially available ROV. This research involves pose graph optimization based on pose estimation by fusing multiple sensors, namely cameras, sonars, and DVLs. The executed trajectory near the hull structure is a simple zigzag pattern, also known as a meander pattern. A noticeable addition is the ability to align previous and years-old inspection scans with recent scans (Ozog et al., 2016). This alignment adds important value to the inspection data since the rate and progress of any deterioration or biofouling of the hull can now be monitored, which in turn can be used to estimate required inspection intervals. Specific to this category is also the focus of the added capability of path planning or execution. Hover et al. (2012) and Hollinger et al. (2012) present a method for full coverage inspection of a hull through redundant roadmaps (Englot and Hover, 2011). They also specifically address the challenging areas around the driveshaft and propeller at the stern of the vessel, and they illustrate the possibility for full hull inspection with a resolution on the order of 10 cm (Hover et al., 2012). The novelty within the planning aspect specifically lies in the redundant roadmaps where previous subsea inspection methods have applied a mostly uniform zigzag pattern. Above sea level, a magnetic wheeled robot—Sparrow—has been developed by Abdulkader et al. (2020) to conduct contact-based ultrasonic thickness inspection. The localization system was based on Marvel Mind beacons attached to the hull of the vessel, and it required line of sight to the robot to provide stable position estimates. The Sparrow can autonomously move in simple zigzag patterns during the inspection, using position estimates from wheel odometry and the beacons. This capability was tested within a 0.7×0.7 m area. Airborne solutions have in recent years been researched as viable solutions for the visual inspection of marine vessels. Examples of this are the AscTec Firefly, the Hummingbird, and the Pelican platforms used by Ortiz et al. (2016b), Bonnin-Pascual and Ortiz (2016a), and Ortiz et al. (2017). To navigate, the system presented by Ortiz et al. (2016b) utilizes LIDARs, cameras, and IMU data from the onboard AscTec flight controller. It makes use of a 2D Hokuyo UST-20LX LIDAR to estimate distances to the surrounding walls, and a 1D LIDAR-Lite to estimate the height above the floor. Experiments were carried out in the cargo hull and the top ballast tanks of a cargo vessel. 2D scan matching was used to align the UAV with the surrounding walls, and, in combination with the LIDAR-lite for height estimate, the system was able to maintain the position of the UAV inside the confined space. The autonomous capabilities of the works of Bonnin-Pascual and Ortiz (2016a) and Ortiz et al. (2017) are similar to that of Ortiz et al. (2016b) due to the employment of the same positioning system to maintain the robot's position next to the wall of the cargo or ballast tank. Ortiz et al. (2017) added a multithreaded Binary descriptor-based Image MOSaicing (BIMOS) approach to create an overview of the inspection surface, using ORB features and Keyframes.

4.4. SAE 3—Conditional Automation

The aerial system used by Bonnin-Pascual et al. (2012) includes self-localization, navigation, and obstacle avoidance. The authors, furthermore, add a Safety Manager system that is built on top of the obstacle avoidance capabilities, by (1) preventing the drone from flying too close to the ceiling, (2) automatically landing the UAV when the battery voltage gets below a threshold or (3) hovering the drone when the wireless connection to its base station is lost. The system is designed for confined spaces within marine vessels, but the experiments are conducted in an office-like environment of approximately $9 \times 8 \times 2.5$ m. Obstacles were simulated using cardboard pillars, and the UAV was successful in planning paths, in 2D, around the obstacles. The system was later updated (Bonnin-Pascual et al., 2015) to make the platform as usable as possible for nonexperts. The level of autonomy matches what was achieved previously (Bonnin-Pascual et al., 2012), but the focus was on the human interaction with the UAV using the Supervised Autonomy approach presented by Cheng and Zelinsky (2001). Bonnin-Pascual et al. (2012) add a human control interface to the UAV, where the operator can overrule part of the automation layers, i.e., path execution. During the human operation, however, the UAV will overrule the operator and perform evasive actions in case obstacles are in the human-executed path. The authors tested the system in an office-like environment, showing the obstacle avoidance capabilities, where the system prevents the operator from flying into a wall. Fang et al. (2017) propose an aerial autonomous system for fire detection in visually degraded confined spaces of marine vessels. In terms of localization, the authors employ an absolute pose estimation method that fuses Visual Inertial Odometry estimates with 6-DOF pose estimates based on point cloud data from an RGB-D camera with a known map of the environment. Online motion planning is applied, which combines A* path planning with a receding horizon control framework for obstacle avoidance. The majority of their tests were conducted in a corridor onboard a vessel, with outbreaks of fires along the corridor. The fires are automatically detected using a FLIR infrared camera using a threshold for temperatures above 100 °C. The UAV was successfully able to automatically navigate along the corridor and through the doorways of the test environment.

4.5. SAE 4—High Automation

The state of the current research has to our knowledge not yet reached [**SAE level 4**] autonomy within marine vessels. However, research within similar environments could reasonably well be applied to raise the autonomy level. The research mentioned in this section is, therefore, mostly of a higher autonomy level than in the area of marine vessels.

Dang et al. (2019) presented a path planning framework for autonomously underground mine exploration based on random trees while also accounting for the robots' endurance limit. Their approach is field-tested on a UAV in an underground mine. Dang et al. (2020a), furthermore, improved the system for underground mine rescue using the same UAV. Their system is capable of autonomously exploring the unknown mine environment and detecting and localizing objects of interest, which in their case were humans in need of rescue. Dang et al. (2020b) further expanded to include other vehicles, more specifically the legged robot ANYmal (Hutter et al., 2016) from ANYbotics AG in Switzerland. ANYmal was also used to perform autonomous inspection inside offshore platforms (Gehring et al., 2021). Here, it was shown that ANYmal could perform some of the same simple inspection tasks as the human surveyors, such as using its manipulator to push buttons, toggle switches and fuses, and turn valves. However, it still lagged behind the humans in simple tasks such as opening and closing doors, which was required due to fire prevention onboard the platform.

4.6. SAE 5—Full Automation

Currently, there is no fully autonomous system, category [**SAE level 5**], which is relevant for vessel inspections.

4.7. Other important aspects

Little research effort within automating inspections has focused on addressing the requirements for surface preparation before an inspection can be performed. For visual and ultrasonic testing, this is most often a thorough cleaning of the surface, which is currently most often done by humans. Kostenko et al. (2019) designed an inspection and cleaning system for removing biofouling on the hull of the vessel.

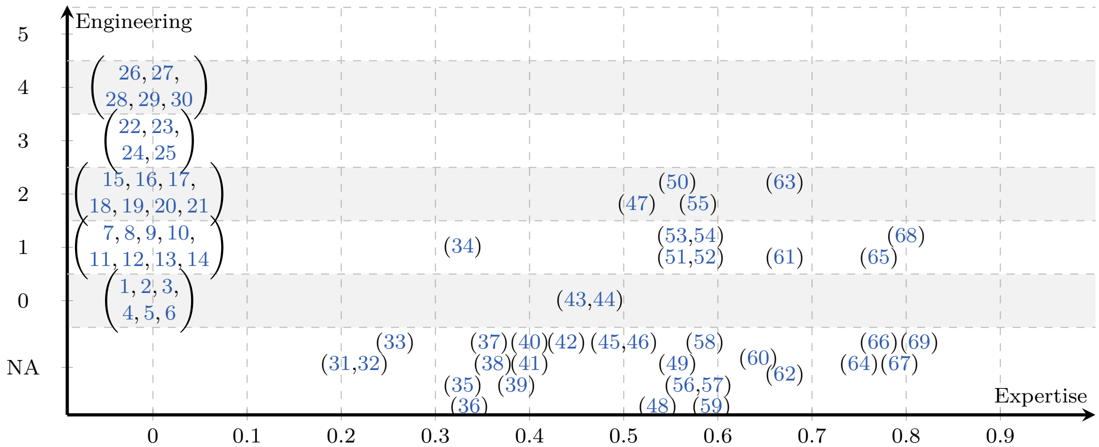
4.8. Summary

Though robotics platforms have been used in the inspection process of marine vessels, many of the platforms do not achieve a high level of autonomy and still rely on human operators for a significant part of the operation. Many of the platforms presented are based on general concepts such as a flying drone or a submarine. This independence also means there is a high probability of being able to transfer a platform from other applications where a higher level of autonomy has been achieved to the marine vessel inspection process. Examples of this were shown to achieve an adopted SAE level of 4—higher than any of the investigated works that specifically target marine vessels.

5. Overall assessment of the state of the art

A visual interpretation of the existing work is shown in Figure 7. From this figure, it is visualized that there is a lack of systems that encapsulate both the engineering and expertise aspect that is necessary to alleviate the human involvement in the inspection process.

It should be noted that some of the references in Figure 7 are not directly trying to solve the challenge of autonomous marine vessel inspection, however they all show some form of potential.



1. (Bandyopadhyay et al., 2018)
2. (Eich and Vögele, 2011)
3. (Huang et al., 2017)
4. (Alkalla et al., 2015b)
5. (Alkalla et al., 2015a)
6. (Garcia-Fidalgo et al., 2015)
7. (Schattschneider et al., 2011)
8. (Chung and Kim, 2018)
9. (Negahdaripour and Firoozfam, 2006)
10. (Milella et al., 2017)
11. (Menegaldo et al., 2008)
12. (Brogaard et al., 2020)
13. (Brogaard et al., 2021b)
14. (Brogaard et al., 2021c)
15. (Ozog et al., 2017)
16. (Ozog et al., 2016)
17. (Kim and Eustice, 2009)
18. (Hover et al., 2012)
19. (Hollinger et al., 2012)
20. (Englot and Hover, 2011)
21. (Abdulkader et al., 2020)
22. (Bonnin-Pascual et al., 2012)
23. (Bonnin-Pascual et al., 2015)
24. (Cheng and Zelinsky, 2001)
25. (Fang et al., 2017)
26. (Dang et al., 2019)
27. (Dang et al., 2020b)
28. (Dang et al., 2020a)
29. (Hutter et al., 2016)
30. (Gehring et al., 2021)
31. (Gardiner and Melchers, 2003)
32. (Qaddoumi et al., 1997)
33. (Zheng et al., 2002);
34. (Maglietta et al., 2018)
35. (Dini and Mura, 2015)
36. (Papachristos and Alexis, 2016)
37. (Siegel and Gunatilake, 1998)
38. (Siegel et al., 1988)
39. (Zaidan et al., 2010)
40. (Avril et al., 2004)
41. (Ji et al., 2012)
42. (Petricca et al., 2016)
43. (Navarro et al., 2010)
44. (Navarro et al., 2013)
45. (Choi and Kim, 2005)
46. (Aijazi et al., 2016)
47. (Ortiz et al., 2018)
48. (Akinfiev et al., 2008)
49. (Bastian et al., 2019)
50. (Ortiz et al., 2016b)
51. (Ortiz et al., 2016a)
52. (Bonnin-Pascual and Ortiz, 2011)
53. (Ozog and Eustice, 2016)
54. (Eich et al., 2014)
55. (Bonnin-Pascual and Ortiz, 2016a)
56. (Bonnin-Pascual and Ortiz, 2016b)
57. (Bonnin-Pascual and Ortiz, 2018)
58. (Fernández-Isla et al., 2013)
59. (Yao et al., 2021)
60. (Yang et al., 2018)
61. (Liu et al., 2018c)
62. (Bonnin-Pascual and Ortiz, 2014)
63. (Ortiz et al., 2017)
64. (Jahanshahi et al., 2011)
65. (Liu et al., 2018a)
66. (Liu et al., 2019)
67. (Hoskere et al., 2020)
68. (Liu et al., 2018b)
69. (Andersen et al., 2020)

Figure 7. The existing works scored on their expertise and engineering aspect. The category NA captures all the works that presented some form of expertise but have not presented a way of collecting the sensory information necessary for a fully autonomous system.

While most of the literature included in this paper tries to solve either the expertise or engineering aspect, some of the works are part of a larger project that collectively tries to solve the challenge of automating the inspection process. Generally, it is these papers consisting of collections of previous work that score high in both expertise and engineering.

Among the highest scoring works are a significant number using UAVs as a robotic platform to reach otherwise inaccessible areas. One reason for this might be the ease of access to these kinds of platforms in combination with the low requirement for specific external environments—i.e., they do not rely on the presence of water and work in nonmetal structures. Though they are limited by their heavy tradeoff between lifting capacity and battery life, they can quickly traverse large areas while carrying lightweight sensor equipment such as cameras. In return, the cameras can provide a large amount of information about the environment where the drone is located and can be used to detect defects. By using stereo vision, the drone can even achieve 3D vision that enables localization of defects (Brogaard et al., 2021a). A general challenge when relying on cameras as the input for detection is the reliability of external lighting. In some areas of a marine vessel, such as in the ballast tanks, there is no natural light, thus the drone has to carry it onboard, further reducing the effective flight time in the case of aerial drones.

Some of the works presented in this paper utilize multiple robotic platforms to perform different parts of the inspection process. This means the platforms can be more specialized in solving one part of the inspection process. It also means that the output of the technologies has to be merged before a complete overview of the vessel condition can be given, thus demanding a higher level of cooperation.

Many of the works reviewed in this paper address capturing sensory information through the use of cameras and drones while also presenting some level of image processing to evaluate the sensory information. Only a few of them address the challenge of capturing image data in areas where there are very poor lighting conditions. Since many areas of modern marine vessels have little to no natural light, any drone has to carry any necessary light sources with it, which complicates the detection. Additionally, none of the methods address the uncertainty associated with detection. That is, the detection's not influencing the behavior of the drone to optimize the ability to accurately do defect quantification—a critical step towards an autonomous solution that provides the necessary level of quantification for the classification society. Similarly, there is a clear trend to use object detectors and segmentation models to provide a deterministic output. By doing so, they fail to encapsulate the ambiguity that is inherently present in visual defect detection where information is only partially observable due to the surface conditions where the defects are located. Instead of these deterministic approaches, one future direction for marine vessel inspection that has to be addressed is a distribution estimation over the detected faults and defects. If a classification society has to rely on the detections without being present, they need access to some form of certainty metric from which they can assess the overall vessel condition without risking a wrongly tuned confidence threshold altering the vessel classification.

Though a wide range of detection models has been tried on defect detection, very little emphasis is put on processing the detections in a human-readable manner, e.g., by converting the mapped detections to the reference frame of the vessel by noting on which longitudinal or web frame the defect is present. This kind of topological representation could also be used for navigational purposes. The vessels are well structured and the layout of all areas to be inspected is usually known in advance. This information is rarely used in combination with active defect detection to optimize the information gathered during the traversal of the inspection areas. Using a topological navigation planner would also alleviate the risk of drifts. If the drone is relying on a high-resolution map representation of the environment, drifting increases the risk of collision with the environment. By using a topological planner that relies only on high-level information such as longitudinal counts, web frame counts, stringer level, etc., in combination with local information like VIO and 3D sensory information, the need for high-resolution maps can be reduced. An instance where relying on internal map representations can be insufficient is when navigating to an unexplored area through a narrow passage. If the map representation is too low, the narrow passage is not visible, or difficult to reliably sample paths during exploration. Simultaneously, a too high map resolution increases the requirement for onboard processing.

6. Conclusion

In this paper, works on autonomous inspection were reviewed and evaluated with respect to a series of metrics defined to indicate how far the state of the art has progressed when compared to the needs of the classification societies. The metrics consist of two parts: expertise and engineering. The purpose of this split was to separate the part of an autonomous system that performs condition assessment of vessels and the part that enables the inspection to be physically carried out.

The metrics defined for the expertise were intended to show how well a given method can assess the types of defects that are typically found during a marine vessel inspection as well as quantify them. Generally, most of the methods struggle to quantify the defects they are able to detect. While the detection of defects is useful as a starting point, it is not sufficient as a replacement for manual inspection.

The adapted SAE taxonomy was used as a metric to evaluate the robotic platforms related to marine vessel inspection. This stepwise taxonomy describes the level of autonomy of each robotic platform where a higher score means a lower level of manual operation involved in the inspection. Some of the robotic platforms achieved a significant level of autonomy.

Though the purpose of this paper was not to perform an in-depth review of the machine learning and locomotion methods used in the literature, we have observed a high correlation between using deep learning techniques in a system and scoring high in our metrics—specifically the expertise one. In combination with flexible robotic platforms, such as UAVs, deep learning has proven to be an effective approach to the marine vessel inspection process.

Based on the analysis done in this paper, we have identified some crucial future research directions within marine vessel inspection and classification: a higher level of quantification, human interpretable defect localization, defect-aware navigation, and the notion of probabilistic inspection. Remote inspection cannot be realistically implemented as an assistive tool for human surveyors unless a higher level of quantification is achieved. By doing so, the expertise level of the solutions would be increased significantly. Additionally, defect localization in a human interpretable manner would be directly usable in the vessel condition documentation. This would help increase the confidence of the surveyor and would reduce the amount of translation that has to be done between users of the new autonomous system and the established classification process. As a further note, there is a lack of navigation methods that incorporate faults and defect detections to increase detection confidence and quantification accuracy, for documentation purposes, or otherwise better coverage of an area under consideration. From the analysis, we also found a lack of works that address the ambiguity of the classification process. Future research should help address this ambiguity by relying less on single binary ground truths as these are both difficult to access and rely on due to residue buildup in the ballast tanks.

We believe that these four areas of research would significantly increase not only the autonomy of marine vessel inspection but also the confidence of the human surveyors that have to rely on the system and ultimately are responsible for the vessel certification.

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