

Atmospheric Corrosion Detection and Management with AI

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ABSTRACT

Atmospheric corrosion is the biggest asset integrity threat to offshore Oil and Gas (O&G) platforms in the Gulf of Mexico (GoM). Manual inspection of an offshore platform's topside equipment is costly, time-consuming, and labor-intensive. Moreover, manual inspection findings are subjective and provide incomplete asset coverage, leading to increased risk of unplanned shutdowns due to missed repairs. Computer vision and machine learning algorithms can be used to detect and classify corrosion, allowing for the objective and comprehensive management of corrosion across a facility. Detected corrosion is associated with equipment and reported, enabling high-risk equipment (i.e., high likelihood and/or consequence of failure) to be targeted for remediation, significantly reducing the risk of unplanned downtime. This paper covers the first-in-industry application of an AI-based system to improve corrosion management and inspection processes. A case study is presented, where the AI-based corrosion management system is deployed across a large offshore O&G platform in the GoM. The impacts of this new technology for corrosion management are demonstrated, in practice. Machine learning and computer vision algorithms are leveraged to greatly improve inspection, maintenance, and management processes, reducing the operating costs and risks associated with offshore O&G platforms.

Key words: atmospheric corrosion, corrosion management, risk-based inspection, inspections, corrosion science and technology.

INTRODUCTION

External corrosion on offshore O&G platforms is one of the biggest threats to asset integrity and its management is a large operational expense. Many operators now implement risk-based assessment (RBA) programs where all equipment is assessed periodically with the aim to reduce operational costs while maintaining integrity. Regulatory codes for offshore platforms in the GoM require a visual inspection of all pressure equipment and piping every five-years. In practice, this can equate to approximately 20% of equipment being inspected per year on a large-sized offshore platform (i.e., a topside weight of around 10,000 tons), with a rolling five-year inspection plan to balance the inspection workload evenly through time. As a result, in a five-year inspection cycle, a platform operator will not have visibility to the condition of the equipment for other times in the inspection cycle (i.e., a single equipment is only inspected once in the five-year cycle). Due to the complexity of equipment and infrastructure lay-out, equipment at-heights, spanning over-water, and difficult to inspect areas, performing equipment inspections can be costly, time-consuming, and yield varying quality of results. Variance in inspections can arise from the inspector's subjectivity, the environmental changes, and the present working conditions around the platform. Inspector's must sometimes access equipment that is difficult to reach or see and making close assessments difficult.

An effective asset integrity program requires full visibility of asset and equipment conditions. Prioritizing the Non-Destructive Examination (NDE) on high consequence-of-failure or high likelihood-of-failure equipment results in effective risk reduction and improved fabric maintenance planning. For instance, high consequence-of-failure equipment (such as a high-pressure gas line) with severe corrosion must be addressed as soon as possible. Further, prioritization of a complementary painting/remediation program is also critical to preventing assets reaching this level of deterioration in the future. By prioritizing the remediation of high-risk assets and optimizing the remediation process, overall the risk decreases significantly, and the cost of remediation and inspection continue to decrease. At scale, this enables operators to reduce their assigned Personnel on Board (PoB) per platform.

The automatic detection of corrosion in images has been explored in recent literature.¹⁻⁸ Ortiz et al.¹ demonstrated the effectiveness of using a single-layer artificial neural network to the detection of corrosion and cracks in ship ballast tanks. Hoang and Tran³ used a Support Vector Machine to classify small tiles of an image as containing rust or no-rust. Petricca et al.² and Nash et al.⁴ trained a Convolutional Neural Network (CNN) to classify an entire image as either containing rust or no-rust, whilst Nash et al.⁵ estimated the required effort for attaining human-level accuracy for corrosion detection by a CNN to be > 65,000 labeled images. Finally, Ferguson et al.,⁶ Majors et al.⁷ and Garcia et al.⁸ leverage CNNs to classify pixels in an image (i.e., semantic segmentation) as either containing rust or not, giving a detailed understanding of the scene.

A case study is presented, where the AI-based corrosion detection and management system is deployed across a large offshore O&G platform in the GoM. The impacts of this new technology for corrosion management are demonstrated, in practice. A case study demonstrates:

- The cost reduction of inspection programs when using of the AI-based system versus traditional manned visual inspections;
- Increased inspection coverage of inspections when using of the AI-based system versus traditional manned visual inspections;
- A decrease in the required Personnel on Board (PoB) an offshore platform to conduct general visual inspections (GVIs);
- The reduction of risk across a platform through the prioritization of inspection and remediation;

- The benefits associated with better prioritization and optimization of painting campaigns; and
- The benefits associated with the improved optimization of platform maintenance.

EXPERIMENTAL PROCEDURE

A terrestrial scanner is used to comprehensively capture inspection data (i.e., 360 degree panoramic images and laser scans) across the topside of an offshore platform. This is completed to a density of approximately one scan every 2.5m. For a large deep-water spar production platform (approximately five 200x200 ft. decks), this requires nearly 14 days with 5 data scanning personnel. The method presented is directly applicable to data from any terrestrial scanner supporting visual and 3D data. An example of a captured panorama is seen in Figure 1a, whilst Figure 1b shows a 3D point-cloud representation of two decks of an offshore platform, made by combining a number of captured scans. The data capture process attempts to cover 100% of the platform surface by carefully planning the scan density and considering corner-cases such as tight spaces, complex pipework, and equipment at heights.

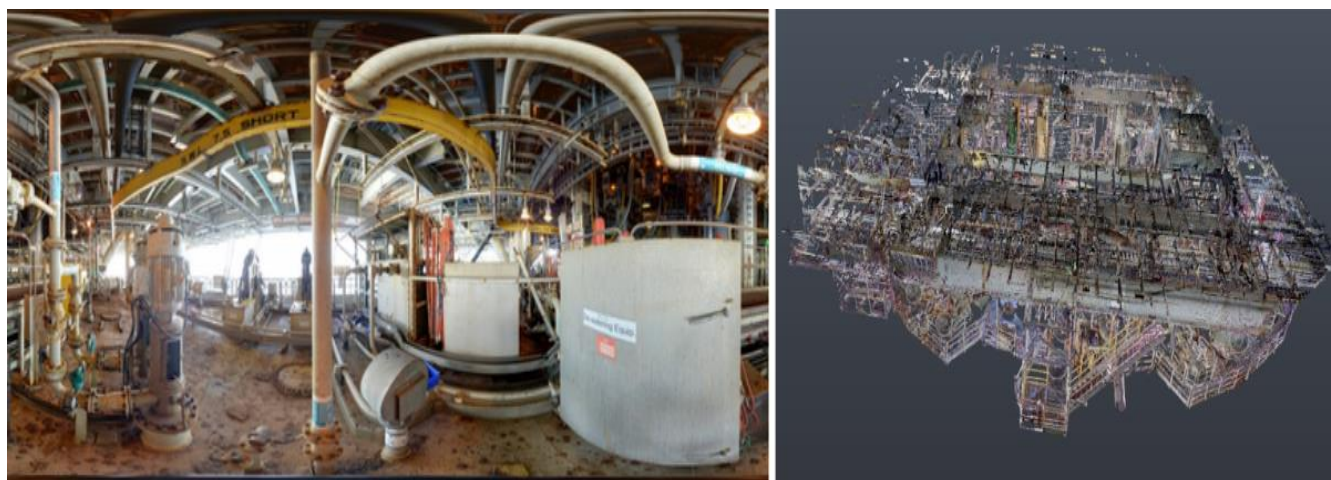


Figure 1: (left) An example of a panorama, and (right) a 3D point cloud representation of two decks of an offshore platform.

All inspection imagery is processed using automated corrosion detection algorithms, which localizes and categorizes corrosion across the facility by severity, according to the authors' previous works.^{6,7} Figure 2 shows an example of detected and classified corrosion, overlaid on inspection imagery, with atmospheric corrosion severity shown by color. A user can virtually 'walk' through the inspection data, and be directed to equipment, such as equipment where heavy corrosion has been detected.

Due to the spacing of scans, equipment often appears in multiple views, i.e., it is common for equipment to be imaged from many angles and ranges. Since all inspection imagery is spatially located within a common frame of reference, it is possible to combine the multiple inspection viewpoints and predictions together to produce a single, comprehensive 3D-visual dataset of the asset, as seen in Figure 3. Combining multiple views has many benefits. For example, if a portion of some equipment piece is obscured from a single scan location, it is often included in neighboring scans. This process reduces the impact of camera obstructions and helps to maximize coverage of the equipment and the platform. Furthermore, corrosion predictions from multiple viewpoints can be merged via various statistical methods to further refine predictions and increase the accuracy of classification. Corrosion detection from multiple perspectives is shown in Figure 3, which shows coverage from three (of 38) separate views, which are combined statistically to produce the aggregate corrosion coverage metrics.