

# On the Use of Robots and Vision Technologies for the Inspection of Vessels: a Survey on Recent Advances

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## Abstract

Vessels are widely used for transporting goods around the world. All cargo vessels are affected by two main defective situations, namely cracks and corrosion. To prevent major damage/accidents, intensive inspection schemes must be carried out periodically, identifying the affected plates for a subsequent repair/replacement. These inspections are performed at a great cost due to the arrangements that allow human inspectors to reach any point of the vessel structure while guaranteeing their physical integrity and respecting all the stipulated safety measures. Technological advances can provide alternatives to facilitate the vessel inspection and reduce the associated cost. This paper surveys approaches which can contribute to the reengineering process of vessel visual inspection focusing on two main aspects: robotic platforms which can be used for the visual inspection of vessels, and computer vision algorithms for the detection of cracks and/or corrosion in images. The different approaches found in the literature are reviewed and classified regarding their key features, what allows identifying the main trends which are being applied so far and those which could mean an improvement in the current visual inspection.

### *Keywords:*

Vessel inspection, Current approaches, Survey, Robotic platforms, Defect detectors

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## 1. Introduction

The seaborne trade increases year after year pushed by the global economic growth and the effectiveness of vessels for transporting goods around the world (United Nations Conference on Trade and Development, 2015). Each cargo category requires from a specific type of vessel, though around 90% of the world fleet belongs to one of the four main vessel types, namely bulk carriers, tankers, container ships and general cargo.

Regardless of its category, a vessel can be affected by different kinds of defects that may appear due to several factors, including structural overload, errors in the vessel design, the use of sub-standard materials, poor alignments

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8 or weldings, hydrodynamic or mechanically induced vibrations and coating breakdown, among others.

9 Roughly speaking, and regardless of its cause, two main defective situations are typically considered: cracks  
10 and corrosion. Cracks generally develop at intersections of structural items or discontinuities (including changes in  
11 thickness) due to stress concentration, although they also may be related to material or welding defects. If the crack  
12 remains undetected and unrepaired, it can grow to a size where it can cause sudden fracture. Therefore, care is needed  
13 to visually discover fissure occurrences in areas prone to high stress concentration.

14 As it is well known, corrosion may affect vessel structures in different forms:

- 15 • *general corrosion*, that appears as non-protective friable rust which can occur uniformly on uncoated surfaces;
- 16 • *pitting*, a localized process that is normally initiated due to local breakdown of coating and that derives, through  
17 corrosive attack, in deep and relatively small diameter pits that can in turn lead to hull penetration in isolated  
18 random places;
- 19 • *grooving*, again a localized process, but this time characterized by linear shaped corrosion which occurs at  
20 structural intersections where water collects and flows; and
- 21 • *weld metal corrosion*, which affects the weld deposits, mostly due to galvanic action with the base metal, and  
22 that are likelier in manual welds than in machine welds.

23 To ensure the integrity of the vessel hull structures, extensive inspection schemes are carried out periodically.  
24 These inspections are currently conducted either as part of Class surveys, performed by a Classification Society  
25 following a set of strict rules which ensure the vessel satisfies seaworthiness criteria, or Condition surveys, which are  
26 less formal procedures commissioned by the vessel owner or the vessel operator to check whether the vessel structures  
27 satisfy the requirements that keep the ship operational.

28 To perform a complete hull inspection, the vessel has to be emptied and situated in a dockyard (and probably in a  
29 dry-dock), where typically temporary staging, lifts, movable platforms, etc. need to be installed to allow the workers  
30 for close-up inspection of all the different metallic surfaces and structures. The items to survey depend on the type  
31 and age of the vessel, as well as the kind of survey that is being carried out. To illustrate the enormity of the inspection  
32 task, the surveying of a central cargo tank on a Very Large Crude Carrier (VLCC) can involve checking over 860 m  
33 of web frames (primary stiffening members) and approximately 3.2 km of longitudinal stiffeners, while the complete  
34 survey to verify the state of the whole vessel can mean the visual assessment of more than 600.000 m<sup>2</sup> of steel.

35 Furthermore, the surveys are on many occasions performed in a potentially hazardous environment with both  
36 flammable and toxic gases and significant heights involved. As a result, although accidents are extremely rare, when

37 they do arise they can have serious consequences. Due to these complications, the total cost of a single surveying  
38 give rise to a very significant amount once you factor in the vessel's preparation, use of yard's facilities, cleaning,  
39 ventilation, and provision of access arrangements. In addition, the owners may experience significant lost opportunity  
40 costs while the ship is inoperable.

41 Infrastructure inspection by means of robots is a line of research that the EU has been lately supporting through the  
42 FP7 and H2020 programmes (projects MINOAS (Eich et al., 2014), INCASS (Ortiz et al., 2017) and ROBINS (Ortiz  
43 et al., 2018), among others) and through specific calls, such as Robotics in Application Areas: b) Innovation Actions  
44 - Robotics for infrastructure inspection and maintenance, ICT-09-2019-2020 (European Commission, 2017).

45 Focusing on the particular case of vessel inspection, this paper reviews technological advances which (at least  
46 potentially) can facilitate such processes. To be precise, this survey reviews contributions on two key fields. Firstly,  
47 Section 2 reviews approaches related to robotic platforms suitable for vessel hull inspection, irrespectively of the  
48 mechanical structure of the device and its locomotion approach (e.g. magnetic crawlers, free-floating vehicles, aerial  
49 platforms, etc). Next, the survey focus on processing the data collected by the robots, particularly as regards defect  
50 detection by visual means. To be more precise, in Section 3, we overview vision-based detection algorithms for the  
51 two aforementioned kinds of defects, i.e. cracks and corrosion. Both sections finalize discussing about the current  
52 trends in these specific research fields. Finally, Section 4 reaches some conclusions on the topics surveyed.

## 53 **2. Robotic Platforms for Inspection**

54 Mobile robotic devices have been widely used for the inspection of infrastructures. In this regard, the robotics  
55 literature contains a number of examples about robots devised for inspecting power transmission lines (Katrašnik  
56 et al., 2010; Pagnano et al., 2013), dams (Ridao et al., 2010; Cruz et al., 2011), bridges (La et al., 2013; Lim et al.,  
57 2014), pipes and sewerage (Mirats and Garthwaite, 2010; Roslin et al., 2012), aircraft skin (Siegel and Gunatilake,  
58 1998; White et al., 2005), etc. In the following sections we focus on those contributions that are of interest for vessel  
59 inspection. In Section 2.1, we revise contributions which describe robotic platforms specifically intended for vessel  
60 hull inspection, including platforms devised for underwater operation and those developed for being used above the  
61 water line, without contemplating aerial platforms. This is because we deal with them separately in Section 2.2, where  
62 these are considered together with other aerial platforms intended for the inspection of any kind of infrastructure, since  
63 they can potentially be useful for vessel inspection.

### 64 *2.1. Robotic Platforms devised for Vessel Hull Inspection*

65 The robotics literature contains several contributions about robots for vessel inspection. Most of them consist in  
66 underwater vehicles for the inspection of the submerged part of the vessel hull. As a first example, the vehicle pre-

67 sented by Lynn and Bohlander (1999) is an underwater Remotely Operated Vehicle (ROV) intended for inspection.  
68 This is a free-floating vehicle which is able to take paint-thickness measurements of the underwater hull using a spe-  
69 cific probe. The *Little Benthic Crawler* (Newsome and Rodocker, 2009) is another remotely operated robot equipped  
70 with a camera suitable for vessel visual inspection. This is a commercial 2-piece robot consisting of a 5-thruster ROV  
71 and a removable 4-wheel drive crawler skid assembly. The latter houses a vortex generator which provides attractive  
72 force on any relatively flat surface. Another example is authored by Ishizu et al. (2012), who present the design and  
73 development of a mechanical contact mechanism that allows an ROV to keep a suitable position and orientation to  
74 improve the visual inspection of the hull.

75 Autonomous Underwater Vehicles (AUV) have the potential for better coverage efficiency, improved survey pre-  
76 cision, and overall reduced need for human intervention. Some AUVs devised for vessel inspection are designed to  
77 attach and crawl over the hull surface. The *Lamp Ray* (Harris and Slate, 1999; D'Amaddio et al., 2001) is an under-  
78 water hull-crawling robot that delivers data on hull plate thickness, form and coating condition. It makes use of an  
79 acoustic beacon positioning system, also known as long-baseline system (LBL), for waypoint navigation, providing  
80 autonomy. A non-contact underwater ultrasonic (US) thickness gauge and different kinds of probes are used to per-  
81 form Non-Destructive Testing (NDT), to sense the hull state. The vehicle can operate in free-swimming mode until  
82 reaching the hull surface. Then, it holds itself using front-mounted thrusters for suction and moves on wheels over  
83 the hull surface, while complex geometry around (e.g. sonar domes, propeller shafts, etc.) is still generally inspected  
84 with a free-swimming ROV.

85 The *AURORA* underwater robot (Akinfiyev et al., 2008) is a hull-crawling robot that can clean a vessel from marine  
86 fouling, while simultaneously inspects the state of the hull by means of a US probe and cameras. It can be operated  
87 in manual mode and in two different automated modes. In the first one, the robot estimates its movement direction  
88 using vision to differentiate the already cleaned areas. In the second autonomous mode, the platform obtains its  
89 relative position by triangulation using three US sources attached to the vessel hull. Similarly, the *HISMAR* robotic  
90 system (Narewski, 2009) is conceived to keep the ship hull clean and free of biofouling in order to increase the ship  
91 propulsion efficiency. The vehicle is also devised to take plate thickness measurements. Similarly to the *AURORA*  
92 robot, the pilot provides control commands via an umbilical with power, control lines and hoses used for bringing  
93 the cleaning wastes to the surface. Position is estimated by dead-reckoning using optical technology to track the two-  
94 dimensional movement over the hull surface. The absolute position estimation makes use of known hull features to  
95 correct the current tracked position using a magnetic sensing system.

96 The *HROV* (Hybrid-ROV) (Ferreira et al., 2013) is an underwater hull-crawling vehicle devised for the ultrasonic  
97 inspection of Floating, Production, Storage and Offloading (FPSO) units. Like the *Lamp Ray*, the *HROV* can also

98 be operated in free-flying mode to reach the hull surface, and then attach itself using the vertical thrusters. For  
99 the displacement over the hull surface, it makes use of two motorized tracks. Its sensor suite includes an altimeter  
100 to measure the distance to the hull, a depthmeter, an Inertial Measurement Unit (IMU) providing acceleration and  
101 attitude information, and a Doppler Velocity Log (DVL) which provides the hull-relative velocity and position (i.e.  
102 dead-reckoning via integration).

103 Apart from the previous mentioned approaches, most of the contributions regarding underwater robots are based  
104 on free-floating platforms which are not attached to the vessel hull. The *CetusII* (Trimble and Belcher, 2002) is a  
105 free-floating AUV which uses a specifically designed LBL acoustic beacon system for navigation around ship hulls  
106 and similar underwater structures. The vehicle uses altimeters to maintain a constant relative distance from the hull,  
107 while the LBL navigation system records its position information along the hull being inspected. This system uses a  
108 transponder net that is deployed over the side of the ship. The inspection of the hull is performed using a forward-  
109 looking imaging sonar. This is a high-resolution sonar which is able to create two-dimensional (2D) acoustic intensity  
110 images.

111 Several approaches try to provide solutions for positioning where LBL systems fail (e.g. in environments with  
112 extreme multipath effects). The *HAUV* (Hovering AUV) underwater robot (Vaganay et al., 2005, 2006; Hover et al.,  
113 2007) employs a DVL for hull-relative navigation and control. This sensor allows locking the AUV onto the ship  
114 hull, maintaining distance and orientation, and computing dead-reckoned coordinates regarding the hull surface. Data  
115 provided by an IMU and a depth sensor are also merged for that purpose. The *SY-2* (Li et al., 2009) and the *RE-*  
116 *MUS* (Packard et al., 2010) AUVs make use of a similar configuration of sensors and actuators. The *REMUS* and the  
117 *HAUV* robots are equipped with a dual-frequency imaging sonar which is able to provide images of the vessel hull  
118 even in turbid water. The unit installed in the *HAUV* is the Dual-Frequency Identification Sonar (*DIDSON*) (Belcher  
119 et al., 2002) which has been also used to create large scale hull mosaics (Reed et al., 2006).

120 Kokko (2007) presents an alternative localization method relying on range measurements taken to surfaces of  
121 known curvature, which belong to the vessel hull. This approach, which is intended to be applied to the *HAUV*  
122 vehicle, is validated in simulation and using a raft robot.

123 The *HAUV* is used again by Walter et al. (2008). In this approach, the *DIDSON* sonar is integrated in a Simultane-  
124 ous Localization and Mapping (SLAM) framework. The latter technique consists in creating an incremental map of an  
125 unknown environment while localizing the robot within this map (Durrant-Whyte and Bailey, 2006). Similarly, Walter  
126 et al. (2008) perform SLAM using an Exactly Sparse Extended Information Filter (ESEIF). This approach needs a  
127 manual selection of feature correspondence in the sonar image due to the device's low resolution and low signal-to-  
128 noise ratio, in comparison with images taken using optical cameras.

129 VanMiddlesworth et al. (2013) present another SLAM-based approach using the *HAUV* and the *DIDSON* sonar.  
130 This approach consists in aligning point clouds gathered over a short time scale using the Iterative Closest Point (ICP)  
131 algorithm. To improve the alignment, the authors present a system for smoothing these “submaps” and removing  
132 outliers. Constraints from submap alignment are integrated into a 6-Degrees of Freedom (DOF) pose graph, which is  
133 optimized to estimate the full vehicle trajectory over the duration of the inspection task.

134 Several approaches are based on computer vision techniques. Zainal Abidin and Arshad (2006) present a system  
135 to help ROV operators by minimizing the task of controlling the camera orientation. The system determines the  
136 orientation of the hull surface and adjusts the camera position to trace the vessel shape. It consists in three laser  
137 pointers and a colour Charge Coupled Device (CCD) camera mounted in the same pan-tilt unit. The angle between  
138 the camera and the surface is calculated by using triangulation of the position of the pixels corresponding to the three  
139 laser spots in the camera image.

140 Negahdaripour and Firoozfam (2006) present a stereo-vision system based on mosaic registration methods. It  
141 is integrated in a free-floating commercial ROV to provide the capabilities for positioning, navigation and mapping  
142 during the automated inspection of a ship hull. The authors provide early results for pool and dock trials.

143 Schattschneider et al. (2011) present an Extended Kalman Filter (EKF) SLAM system using a stereo camera  
144 to estimate the position and orientation of an AUV. In their work, they provide laboratory results using a movable  
145 measurement apparatus fitted with a stereo camera pointing at the floor, where a printout of a ship hull image is  
146 placed.

147 Hover et al. (2012) increase the capabilities of the *HAUV* combining hull-relative DVL odometry, *DIDSON* imag-  
148 ing sonar and monocular camera constraints into a pose-graph SLAM optimization framework to produce an accurate  
149 and self-consistent three-dimensional (3D) trajectory estimate of the vehicle. More specifically, they apply sonar and  
150 vision-based SLAM processes (Johannsson et al., 2010; Kim and Eustice, 2009), and combine them via Incremental  
151 Smoothing and Mapping (iSAM) (Kaess et al., 2008), to create a single comprehensive map. The resulting vehicle is  
152 able to autonomously cover the whole vessel hull, including complex 3D structures as shafts, propellers and rudders.

153 Kim and Eustice (2013) improve the vision-based pose-graph SLAM method presented some years before (Kim  
154 and Eustice, 2009). They introduce an online Bag-of-Words (BoW) measure for intra and inter-image saliency in  
155 order to identify informative key-frames. Ozog et al. (2016) use a similar technique in underwater saliency-informed  
156 SLAM to relocate the *HAUV* in a multiple session hull inspection. Using this approach, a single-session SLAM result  
157 is initially used as a prior map for later sessions, while the robot automatically merges the multiple surveys into a  
158 common hull-relative reference frame. To perform the relocalization step, the authors use a particle filter to leverage  
159 the locally planar representation of the ship hull surface. Furthermore, Generic Linear Constraints (GLC) allow

160 managing the computational complexity of the SLAM system as the robot accumulates information across multiple  
161 sessions. The authors provide results for 20 SLAM survey sessions for two large vessels over the course of days,  
162 months, and even up to three years.

163 Ozog and Eustice (2015) combine a stereo camera and a DVL into a SLAM framework allowing to localize the  
164 *HAUV* into a 3D Computer-aided Design (CAD) model of the ship hull. Furthermore, this method labels visually-  
165 derived 3D shapes based on their deviation from the nominal CAD mesh. This deviations, which can be caused by  
166 biofouling, are added into the prior mesh.

167 Other approaches focus on the use of robots magnetically attached to the vessel hull, what makes feasible the  
168 inspection above the water line. Despite the fact that some of them are able to estimate their pose (position and ori-  
169 entation), they are basically remotely operated. *SIRUS* (Menegaldo et al., 2008) and *MARC* (Bibuli et al., 2012) make  
170 use of magnetic tracks to attach to the dry part of the hull. They both are equipped with US thickness measurement  
171 sensors and cameras. *SIRUS* is also able to roughly estimate its position using an EKF to fuse the wheel odometry  
172 and the accelerations provided by the IMU.

173 *MIRA* is a fast-deployment lightweight crawler (Eich and Vögele, 2011; Fondahl et al., 2012; Ahmed et al., 2015)  
174 which has been developed within the same research project as *MARC*, that is to say, the MINOAS project (Ortiz et al.,  
175 2010; Eich et al., 2014). Since self-localization is not feasible in such a lightweight vehicle, the position of the robot  
176 is estimated using an external 3D tracking system that consists of a camera and a laser range finder mounted on a  
177 pan-tilt unit.

178 Finally, some approaches are intended for the inspection of the submerged part of the hull using magnetic at-  
179 tachment. A first example in the *SHIV* (Nicinski, 1983) platform, which consists in an underwater crawler provided  
180 with 6 magnetic wheels. Similarly, the vehicle presented by Carvalho et al. (2003) is aimed for US-based underwater  
181 inspections of FPSO units.

## 182 2.2. Aerial Robotic Platforms for Inspection

183 The civilian use of Unmanned Aerial Vehicles (UAV) for removing personnel from hazardous situations has grown  
184 significantly in recent years. One particular sector of application is visual inspection. Among the different aerial  
185 platform configurations, the Small Unmanned Aerial Systems (SUAS) with capabilities for Vertical Take-Off and  
186 Landing (VTOL), such as the multicopters (in the form of quadrotors, hexarotors, octorotors, etc), ducted-fans or  
187 coaxial rotor-based helicopters, are the most used platforms. These platforms, sometimes called Micro-Aerial Vehicles  
188 (MAV), present high maneuverability and are able to operate in confined spaces, including indoor environments. These  
189 platforms are typically characterized by a limited payload and autonomy, as well as by small size and reduced cost.

190 The article by Huerzeler et al. (2012) presents some scenarios for industrial and generic visual inspection using  
191 aerial vehicles, while the platform requirements are discussed as well. Additionally, Morgenthal and Hallermann  
192 (2014) provide further analysis about UAV properties for visual inspection, focusing on the prevention of image  
193 degradation due to the vehicle movement.

194 Several approaches provide solutions for visual inspection using teleoperated MAVs fitted with cameras. By  
195 way of example, Sampedro et al. (2014) present a supervised classification approach for power tower detection and  
196 classification in images taken using an aerial vehicle. The same classifier is combined with visual tracking techniques  
197 by Martinez et al. (2014) to track the detected tower across the subsequent images. Roberts (2016) uses a corrosion  
198 detector based on colour to detect corroded areas in images taken using a MAV. Two different UAVs are used by Quater  
199 et al. (2014) for the inspection of photovoltaic plants using colour and thermal cameras. Hallermann and Morgenthal  
200 (2014) and Ellenberg et al. (2016) address the visual inspection of bridges using UAVs. Another example is provided  
201 by Eschmann et al. (2012), where an octocopter is used to collect images from building facades. In this approach,  
202 the recorded images are stitched together using a mosaicing algorithm, and the final mosaic is analysed to detect the  
203 presence of cracks. Another approach for building crack detection is presented by Choi and Kim (2015).

204 When flying outdoors, MAVs can operate without human intervention thanks to inertial sensors and GPS (Global  
205 Positioning System). By way of example, Campo et al. (2016) present a system for the autonomous navigation of a  
206 low cost quadrotor in open environments, performing a complete coverage of the area. The system is intended for  
207 applications such as precision agriculture or environmental monitoring. To navigate, the vehicle estimates its pose  
208 using an EKF, combining GPS and IMU data.

209 Nevertheless, the infrastructures to be inspected are usually situated in GPS-denied environments where other  
210 external positioning systems, such as motion tracking systems, can not be installed. For this reason, aerial platforms  
211 for inspection usually must estimate their state (attitude, velocity and/or position) relying on inner sensors and, on  
212 many occasions, using on-board computational resources.

213 The rest of this section tries to provide an horizontal view of the different sensors and techniques applied to the  
214 visual inspection using MAVs. We focus on those approaches that go beyond teleoperation and/or pure GPS-based  
215 positioning. The aim is not to be complete, but to show the different trends.

216 A widely used sensor is the Light Detection and Ranging (LiDAR) device, also known as laser scanner. The  
217 use of this sensor, inherited from ground robotics, allows MAVs for positioning (and sometimes mapping), while a  
218 camera is typically used for the inspection task. In combination with GPS and IMU data, Serrano (2011) proposes  
219 using LiDAR data for culvert inspection using a MAV. The idea is to operate the robot outdoors, taking off from a  
220 military vehicle, and positioning the MAV in front of the culvert entrance, making an intensive use of GPS data. To



221 perform the inspection inside the culvert, where GPS signal is probably not received, the system estimates the MAV  
222 state combining the data provided by the LiDAR sensor with IMU and GPS data within an EKF. Then, the operator  
223 can use a Pan-Tilt-Zoom (PTZ) camera to perform the inspection.

224 Michael et al. (2012) make use of a MAV fitted with a LiDAR and an RGB-D (Red-Green-Blue-Depth) sensor  
225 for collaborative mapping of earthquake-damaged buildings. In this approach, the MAV collaborates with two ground  
226 vehicles to create a 3D map of the different floors inside the building. In a first stage, a primary ground vehicle creates  
227 a 3D map of the environment, using a 3D laser scanner. A secondary ground vehicle carries the MAV to the areas  
228 where debris or other obstacles prevent the ground vehicles to keep going. Then, the aerial vehicle is operated through  
229 those areas and completes the 3D map. Different laser-based positioning and SLAM algorithms are used to perform  
230 the complete mission.

231 Satler et al. (2014) also use a LiDAR for positioning and mapping on-board a MAV intended for the visual  
232 inspection of equipment and structures in constrained spaces. The authors make use of a particle filter-based imple-  
233 mentation of SLAM (FastSLAM 2.0) to merge the data provided by the LiDAR device with IMU data. The vehicle  
234 is also equipped with two sonars, one at the top and one at the bottom, to detect upper and lower obstacles as well  
235 as to measure distances during the ascending inspection flight and during the take-off and landing procedures. The  
236 proposed platform include a PTZ camera and several LEDs (Light-Emitting Diode) for the visual inspection.

237 McAree et al. (2016) discuss the development of a semi-autonomous inspection drone capable of maintaining a  
238 fixed distance and relative heading to the inspected wall using a LiDAR. The vehicle operates in semi-autonomous  
239 mode so that the pilot can concentrate on the inspection task, while the MAV is in charge of performing the challenging  
240 task of distance keeping without pilot input. Within this approach, the authors propose a Model Based Design (MBD)  
241 framework to test the distance and yaw controllers in simulation, prior to using them in real world flights.

242 One of the main drawbacks of using laser scanners in aerial robotics is the relatively heavy weight and ele-  
243 vated power consumption. Recent advances in computational power and CMOS (Complementary Metal-Oxide-  
244 Semiconductor) camera technology have made it possible to use computer vision technologies for state estimation  
245 on MAVs. Many approaches fuse visual (typically stereo) and inertial data to estimate the vehicle state. An example  
246 is provided by Burri et al. (2012), which consists in a visual-inertial motion estimation system for the visual inspection  
247 of industrial environments such as thermal power plant boiler systems. This approach makes use of a sensor compris-  
248 ing an on-board stereo camera augmented with an IMU. This sensor combines measurements of linear accelerations  
249 and angular velocities with pose measurements in a stochastic cloning EKF. The authors also provide two different  
250 strategies for trajectory control which are robust to external disturbances, inaccurate position estimates and delays.  
251 While the experiments presented in this paper are performed in a mock environment, Nikolic et al. (2013) show some

252 results obtained inspecting a boiler system with a more evolved version of the visual-inertial sensor.

253 Omari et al. (2014) propose a navigation system that is built around the commercial version of the previous  
254 mentioned visual-inertial system, the *VI-sensor* (Nikolic et al., 2014). This approach estimates both the trajectory  
255 of the UAV as well as a 3D map consisting of a sparse set of landmarks. The system can also generate a dense 3D  
256 reconstruction in post-processing executing the odometry pipeline over all available visual-inertial data.

257 Gohl et al. (2014) combine the *VI-sensor* with two additional CMOS cameras and a LiDAR sensor for the visual  
258 inspection and 3D reconstruction of underground mines. In this approach, a pilot manually operates the MAV through  
259 the mine to record sensor data. This is post-processed in order to check the feasibility of flying autonomously with  
260 the proposed system and sensors. The experiments performed allow concluding that the vehicle has to be protected  
261 from dust and water to operate inside mines, what will increase the platform weight and decrease its autonomy.  
262 Furthermore, due to the lack of a wireless communication system able to operate throughout an entire mine, the  
263 vehicle has to be autonomous, detecting problems and deciding by itself which solution it should follow.

264 Sa et al. (2015) present a visual-inertial aided VTOL platform for the visual inspection of pole-like structures,  
265 such as light and power distribution poles. The authors present two different approaches for the control system: a  
266 Position-Based Visual Servoing (PBVS) using an EKF and an estimator-free Image-Based Visual Servoing (IBVS).  
267 An additional contribution is the use of shared autonomy to permit an un-skilled operator to easily and safely perform  
268 the inspection using a MAV. The system, which makes use of monocular visual features (lines) and inertial data for  
269 the pole-relative navigation, is in charge of maintaining a safe distance and rejecting environmental disturbances, such  
270 as wind gusts.

271 Optical flow techniques have been also applied to visual inspection using MAVs. Lippiello and Siciliano (2012)  
272 present an autonomous wall inspection control employing optical flow information provided by a stereo camera. Using  
273 this approach, the inspection velocity along the surface is controlled, as well as the orthogonal distance and the relative  
274 yaw angle between the UAV and the observed plane. The authors provide simulation experiments showing the good  
275 performance of the control strategy.

276 Høglund (2014) addresses the use of optical flow for inspecting wind turbines and buildings. The author evaluates  
277 two different optical flow methods for local navigation as well as discusses about its application in tracking a moving  
278 object and estimating the angular velocity. Furthermore, this approach makes use of Hough transform to detect straight  
279 lines when there are no features to track and the optical flow techniques fail. The detected lines allow computing the  
280 relative angles between blades (in wind turbines) or windows (in buildings), which can be used in the orientation  
281 control. While all these techniques are intended to be applied on a hexacopter, they are only evaluated in simulation.

282 Katrašnik et al. (2010) present a survey of mobile robots for distribution power line inspection. It includes dif-

283 ferent computer vision techniques used on-board UAVs for camera stabilization, pole tracking and automated defect  
284 detection. Regarding UAV configuration, two different approaches are reviewed. The first one consists in a ducted-fan  
285 rotorcraft (Jones, 2005) which is able to estimate its position and attitude from an image of three conductors of the  
286 power transmission line using the Hough transform. The second reviewed approach consists in an autonomous heli-  
287 copter (Campoy et al., 2001) which is able to fly along power line using a vector-gradient Hough transform for cable  
288 detection and stereo vision for determining the position of the cable relative to the helicopter.

289 Máthé and Buşoniu (2015) survey vision and control methods that can be applied to low-cost UAVs intended  
290 for visual inspection. Regarding vision-based methods, they overview some techniques for (a) motion tracking and  
291 object detection using feature detection/description, (b) motion estimation using optical flow, (c) camera (and vehicle)  
292 motion control using visual servoing, and (d) vision-based SLAM. Furthermore, they discuss applications related to  
293 infrastructure inspection and provide some contributions for railway inspection selecting the appropriate vision and  
294 control technique to tackle this problem.

295 Inspection tasks sometimes require physical contact with the inspected surface or structure. In Marconi et al.  
296 (2012) article, the authors present two MAV prototypes for contact-based inspection. The first relies upon a ducted-  
297 fan aeromechanical principle, while the second one relies upon a coaxial rotor principle. These vehicles are equipped  
298 with a lightweight manipulator, specifically devised to move NDT sensors according to the input provided by the  
299 operator, and contact sensors, used to detect physical interactions with the surrounding environment. The human-  
300 robot interface makes use of a haptic device and augmented reality. The paper reports on some experiments using a  
301 motion tracking system to estimate the MAV state.

302 Similarly, Jimenez-Cano et al. (2015) present a MAV equipped with a robotic arm attached to the top of the body.  
303 The authors discuss the potential of this setup for inspecting structures such as bridges from the underside. This  
304 approach presents the dynamic model of the entire system, the non-linear controller implemented, and the first flight  
305 experiments performed under a bridge and contacting its surface with a sensor head located at the arm.

306 Alexis et al. (2016) present a control framework to provide a MAV with physical interaction capabilities. The  
307 authors also propose a contact-based inspection planner which computes the optimal route within waypoints while  
308 avoiding any obstacles or other occupied zones on the environmental surface. The resulting MAV is able to perform  
309 complex contact-based tasks, e.g. “aerial writing” or interactions with non-planar surfaces. This approach has been  
310 validated using pose estimates from a motion capture system, while its performance using on-board sensors (like  
311 cameras or LiDARs) has not been evaluated yet.

312 Also related with contact-based inspection, Cacace et al. (2015) propose a high-level control system to allow a  
313 UAV to autonomously perform complex tasks in close and physical interaction with the environment. This system

314 combines hierarchical task decomposition, mixed-initiative control and path planning techniques to allow reactivity  
315 and sliding autonomy. The approach is evaluated in a physical inspection task and in a visual inspection task, both  
316 performed under laboratory conditions.

317 As it happens with the last mentioned approaches, some works focus on issues such as the control strategy, task  
318 planning or path planning, disregarding the sensor suite and the MAV state estimation. Another example is provided  
319 by Wu et al. (2012), where the authors propose an MBD framework for planning efficient and robust behaviours for  
320 power tower inspection. This approach makes use of reinforcement learning to find an optimal policy to guide a MAV  
321 while visiting the target viewing regions along the power tower. The authors provide simulation experiments showing  
322 the performance of this framework when the vehicle is flown in the presence of wind gusts and stochastic noise. A  
323 last example, by Santamaria and Andrade (2014), presents a task oriented control strategy for a quadrotor equipped  
324 with a robotic arm and a camera attached to its end-effector. This approach describes a hierarchical control law to  
325 allow performing visual servoing (primary task) while other tasks (secondary tasks) to minimize gravitational effects  
326 or undesired arm configurations are also running. Successful results are presented in simulation.

327 Regarding aerial platforms specifically devised for vessel visual inspection, the robotics literature contains just  
328 a short list of approaches. Bonnin-Pascual et al. (2012) present a fully-autonomous quadcopter which employs a 30  
329 m-range LiDAR to estimate its position inside the cargo hold under inspection. This platform was developed within  
330 the project MINOAS (Ortiz et al., 2010; Eich et al., 2014). It makes use of both odometry and SLAM processes for  
331 position estimation, while two mirrors are used to deflect part of the laser scans to estimate the distance to the ground  
332 and to the ceiling. The vehicle is operated using a “mission description file” which specifies a list of waypoints. This  
333 approach assumes that vertical structures that are found in vessel holds are quite similar along their full extent. The  
334 Dynamic Window Approach (DWA) (Fox et al., 1997) is used for navigation and obstacle avoidance in the horizontal  
335 plane. In a later work (Ortiz et al., 2014), the system was extended to integrate a monocular visual odometer using a  
336 ground-looking camera. In this approach, the visual odometer is selected, instead of the laser-based estimator, when  
337 the platform performs vertical motion.

338 The same authors describe a different approach as part of the research performed within the project INCASS (Ortiz  
339 et al., 2017). This is based on the use of the *Supervised Autonomy* paradigm, which allows the user/pilot to concentrate  
340 on the task at hand, issuing displacement commands using a gamepad or a joystick, while the platform is in charge  
341 of all the safety-related matters, such as obstacle avoidance. Within this framework, the control pipeline does not  
342 require from the estimation of the robot position, which may be difficult to obtain accurately, but only the estimation  
343 of its velocity (in the three axes) and height. To estimate the vehicle speed, two optical flow sensors are employed,  
344 one looking downwards and the other looking forward, which respectively supply velocity estimations with regard to

345 the floor and to the inspected wall. The flight height is estimated using a laser altimeter. Furthermore, the control  
346 architecture implements a set of robotic behaviours in charge of increasing the platform autonomy during the operation  
347 (e.g. the *go-ahead* behaviour makes the vehicle track the indicated speed until an obstacle is reached or the user  
348 issues a different displacement command). It is worth mentioning that images collected using such a device are later  
349 processed searching for corrosion.

350 A more evolved version of this framework allows configuring different sensor suites depending on the payload  
351 capabilities of the MAV and the environmental conditions (Bonnin-Pascual and Ortiz, 2016; Bonnin-Pascual et al.,  
352 2019). To be precise, the authors propose to replace/combine the optical-flow sensors with a 20 m-range LiDAR  
353 to estimate the vehicle velocity. The latter device allows operating in dark environments (i.e. closed cargo holds  
354 or water ballast tanks) though requires a larger payload capacity (see also Ortiz et al. (2016); Bonnin-Pascual et al.  
355 (2017)). The combination of both sensors (LiDAR and optical-flow sensors) allows the operation in corridor-like  
356 environments, where the LiDAR are typically affected by the so-called “canyoning effect”. Despite the control system  
357 does not require an estimate of the position, a laser-based SLAM method is used to obtain the vehicle coordinates  
358 necessary for tagging the images taken during the inspection. In the aforementioned works, such a framework is  
359 described as for its integration onboard commercial platforms with different configurations and payload capabilities,  
360 and it is evaluated both under laboratory conditions and during real vessel inspection campaigns.

361 Fang et al. (2017) describe another approach involving a MAV operating inside a vessel. This does not deal with  
362 the visual inspection of vessel structures but it focuses on the design of a MAV capable of autonomously navigating  
363 through a ship to aid in fire control. To be precise, the vehicle is able to navigate in dark environments (potentially full  
364 of smoke) looking for fires, measuring heat by means of a thermal camera and locating any personnel along the way.  
365 To do that, this approach combines an odometry estimation method using depth images provided by an RGB-D camera  
366 with inertial data from an IMU. The result is later introduced into a particle filter to perform real-time localization in  
367 a given 3D map. Furthermore, the authors discuss a motion-planning method for computing a collision-free trajectory  
368 for navigating in narrow and/or dynamic environments. The entire framework is tested both inside their laboratory  
369 and in a constrained shipboard environment.

### 370 2.3. Discussion

371 Table 1 summarizes the main features of the robotics platforms for vessel inspection reviewed throughout Sec-  
372 tion 2.1. They are sorted by year of publication. As can be observed, recent approaches for underwater systems focus  
373 on autonomous vehicles (AUV) instead of on teleoperated platforms (ROV). The boom of vision-based perception,  
374 pushed by the high-computational capabilities of current processors and Graphical Processing Units (GPU), makes  
375 cameras the most used devices to obtain that level of automation. Data provided by these sensors is usually merged

376 into EKF and/or SLAM processes with data provided by other sensors typically used in underwater robotics, such  
377 as DVL or sonar. Regarding approaches for above-water inspection with crawlers, 3D position estimation becomes  
378 a hard task especially when the robotic platform traverses between plates of different orientations (wheel odome-  
379 try tends to fail in such situations). For this reason, existing approaches focus on teleoperated platforms where the  
380 position estimation (if any) is used for informing the user/pilot but not for feeding a position control algorithm.

381 Similarly, Table 2 summarizes all the aerial platforms for inspection reviewed in Section 2.2. They are also sorted  
382 by year of publication. As previously mentioned, the reviewed approaches are potentially useful for inspecting (at least  
383 certain areas of) vessels. Most contributions are from the last decade, what is probably due to the reduction in size of  
384 computation boards, which in turn has contributed to the popularization of MAVs (i.e. small-size platforms). Among  
385 the different configurations, quadcopters and hexacopters are the most used. As it happens with non-aerial platforms,  
386 the majority of the aerial approaches make use of vision systems for the state estimation, using different SLAM and/or  
387 KF approaches for computing the platform state. Such vision systems can be based on monocular cameras, stereo  
388 rigs, RGB-D cameras or optical flow sensors. Another sensor which is highly used in aerial robotics is the LiDAR.  
389 This results useful in dark environments where vision systems may fail, though typically require higher payload  
390 capabilities. Several of the different approaches combine the data provided by the selected main sensor with 3-axis  
391 motion data supplied by an IMU (i.e. linear accelerations and orientation) to improve the platform state estimation.  
392 Regarding the autonomy level, some approaches focus on fully autonomous aerial platforms while other tackle the  
393 idea of shared or supervised autonomy. This last operating paradigm allows the human/inspector to interactively  
394 command the platform, what results interesting having into account the kind of task he/she is performing.

Table 1: Approaches for vessel hull inspection using robotic platforms.

Reference	Name	Vehicle type	Sensor suite/technique	
			Navigation	Inspection
Nicinski (1983)	SHIV	ROV ⊗	—	cam/US/mag
Harris and Slate (1999), D’Amaddio et al. (2001)	Lamp Ray	AUV ⊙/≈	LBL	US/mag
Lynn and Bohlander (1999)	—	ROV ≈	—	mag
Trimble and Belcher (2002)	CetusII	AUV ≈	LBL+alt	sonar
Carvalho et al. (2003)	—	ROV ⊗	—	US
Vaganay et al. (2005, 2006), Hover et al. (2007)	HAUV	AUV ≈	DVL+IMU +depth	sonar
Negahdaripour and Firoozfam (2006)	Phantom XTL*	AUV ≈	stereo odo	cam
Kokko (2007)	—	AUV ≈	range	—
Akinfiev et al. (2008)	AURORA	AUV ⊙	opt odo/LBL	US/cam
Menegaldo et al. (2008)	SIRUS	ROV <sup>†</sup> ⊗	EKF: IMU +wheel odo	US/cam
Walter et al. (2008)	HAUV	AUV ≈	SLAM: sonar	sonar
Li et al. (2009)	SY-2	AUV ≈	DVL+IMU +depth	—
Narewski (2009)	HISMAR	AUV ⊙	opt odo +mag lmk	US
Newsome and Roderker (2009)	LBC	ROV ⊙/≈	—	cam
Packard et al. (2010)	REMUS	AUV ≈	DVL+IMU +depth	sonar
Eich and Vögele (2011), Fondahl et al. (2012), Ahmed et al. (2015)	MIRA	ROV <sup>†</sup> ⊗	3D tracker	cam
Schattschneider et al. (2011)	—	—	EKF SLAM: stereo	stereo
Bibuli et al. (2012)	MARC	ROV <sup>†</sup> ⊗	—	US/cam
Hover et al. (2012)	HAUV	AUV ≈	SLAM: DVL +sonar+cam	sonar/cam
Ishizu et al. (2012)	LBV150*	ROV Δ/≈	—	cam/stereo
Ferreira et al. (2013)	HROV	AUV Δ/≈	depth+alt +IMU+DVL	US
Kim and Eustice (2013)	HAUV	AUV ≈	SLAM: cam	sonar/cam
VanMiddlesworth et al. (2013)	HAUV	AUV ≈	SLAM: sonar	sonar
Ozog and Eustice (2015)	HAUV	AUV ≈	SLAM: stereo +DVL	sonar/cam
Ozog et al. (2016)	HAUV	AUV ≈	SLAM: cam	sonar/cam

**Name:** \* indicates a commercial robot used for testing.

**Vehicle type:** <sup>†</sup>/non-underwater vehicle, ⊗/magnetic crawler, ⊙/vehicle attached using suction, Δ/vehicle attached using thrusters and ≈/free-swimming vehicle.

**Sensor suite/technique:** alt/altimeter, cam/camera, depth/depthmeter, mag/magnetic probe, mag lmk/magnetic landmark, odo/odometry, opt/optical and US/ultrasound probe.

Table 2: Representative approaches for vessel hull inspections using specifically aerial platforms.

Reference	Infrastructure	Type	Sensors/tech.	Output
Campoy et al. (2001)	Power line	Heli.	st	img
Jones (2005)	Power line	DF	cam.	img
Serrano (2011)	Culvert	4C	EKF: LiDAR +GPS+IMU	img
Eschmann et al. (2012)	Building facade	8C	—	img+mosaic +cracks
Michael et al. (2012)	Building	4C	SLAM: LiDAR +RGB-D+IMU	3D map
Bonnin-Pascual et al. (2012)	Vessel str.	4C	SLAM: LiDAR +IMU	img+cracks +corrosion
Burri et al. (2012)	Boiler system	4C	EKF: st+IMU	img
Lippiello and Siciliano (2012)	Wall	Sim.	opt flow: st+IMU	img
Marconi et al. (2012)	Contact	DF/Coax.	IMU, contact	phys int
Wu et al. (2012)	Power tower	Sim.	—	img
Nikolic et al. (2013)	Boiler system	4C	EKF: st+IMU	img
Sampedro et al. (2014)	Power tower	—	—	img+tower
Martinez et al. (2014)	Power tower	—	—	img+tower
Quater et al. (2014)	Photovolt. pl.	Hyb./6C	—	img+thermal
Hallermann and Morgenthal (2014)	Bridge	8C	—	img
Satler et al. (2014)	General	4C	SLAM: LiDAR +IMU, 2 US	img
Omari et al. (2014)	General	6C	EKF: st+IMU	3D recons
Gohl et al. (2014)	Mine	6C	EKF: st+IMU, 2 cam., LiDAR	3D recons
Høglund (2014)	Wind turbine /Building	6C/Sim.	opt flow: cam. +IMU+2 US	img
Santamaria and Andrade (2014)	General	4C/Sim.	—	img
Ortiz et al. (2014)	Vessel str.	4C	SLAM: LiDAR +IMU/vis odo.	img
Choi and Kim (2015)	Building	6C	—	img+cracks
Sa et al. (2015)	Pole-like str.	6C	IBVS/PBVS: cam.+IMU	img
Máthé and Buşoniu (2015)	Railway	4C	cam.	img.+track
Jimenez-Cano et al. (2015)	Bridges, etc.	8-4C	—	phys int
Cacace et al. (2015)	Contact	DF/4C	cam./st+IMU	phys int/img
Bonnin-Pascual et al. (2015) Ortiz et al. (2015)	Vessel str.	4C/6C	opt flow	img+ corrosion
Roberts (2016)	Metallic str.	4C	—	img+corrosion
Ellenberg et al. (2016)	Bridge	4C	—	img
Campo et al. (2016)	Open env.	4C	EKF: GPS+IMU	img
McAree et al. (2016)	Wall	8C	LiDAR	img
Alexis et al. (2016)	Contact	4C	motion tracking	phys int
Bonnin-Pascual and Ortiz (2016) Bonnin-Pascual et al. (2019)	Vessel str.	4C/6C	KF: opt flow+ LiDAR+IMU	img+ defects
Fang et al. (2017)	Shipboard env.	4C	Part. filter: RGB-D vis odo+IMU	thermal +fire

**Type:** Heli./helicopter, DF/ducted-fan, 4C/quadcopter, 6C/hexacopter, 8C/octocopter, 8-4C/octoquad Coax./coaxial rotor, Hyb./hybrid and Sim./simulation.

**Sensors/tech.:** st/stereo rig, cam/camera, opt flow/optical flow and vis odo/visual odometry.

**Output:** img/image, phys int/physical interaction, thermal/thermal image and recons/reconstruction.



### 395 **3. Vision-based Defect Detection Algorithms**

396 Visual inspection is one of the predominant methods used in quality/integrity assessment procedures. It is a  
397 subjective process that relies on an inspector's experience and mental focus, making it highly prone to human error.  
398 The development of automated inspection technology can overcome these shortcomings.

399 Previous approaches on automatic vision-based defect detection can be roughly classified into two big categories.  
400 On the one hand, there are lots of contributions on industrial inspection and quality control; that is to say, algorithms  
401 that are in charge of checking whether the products that result from an industrial manufacturing process are in good  
402 condition. These methods assume a more or less confined environment where the product to be inspected is always  
403 situated in a similar position, while lighting conditions are controlled as well. Some examples of these techniques are  
404 collected in Chin and Harlow (1982); Newman (1995); Malamas et al. (2003); Xie (2008).

405 On the other hand, several other contributions focus on visual inspection techniques to ensure the integrity of  
406 elements or structures that have been subjected to some kind of effort or stress. These methods are typically included  
407 in periodical surveys to assess the need of maintenance operations. In this group, which include vessel hull inspection,  
408 we can find algorithms for crack detection on concrete surfaces (Yamaguchi and Hashimoto, 2010), defect detection  
409 on bridge structures (Jahanshahi et al., 2009), aircraft surface inspection (Siegel and Gunatilake, 1998; Mumtaz et al.,  
410 2010), etc.

411 The majority of the algorithms from both categories have been devised for the detection of a specific defect on  
412 a particular material or surface, while much less methods deal with unspecified defects on general surfaces (some  
413 examples are Amano (2006); Peres Castilho et al. (2006); Jia et al. (2004)).

414 Regarding the particular case of vessel inspection, in the following sections we review approaches for the detection  
415 of the main defective situations that may arise on metallic structures, namely cracks and corrosion. Among them, we  
416 focus on those which solely use images as input.

#### 417 *3.1. Algorithms for Crack Detection*

418 This section reviews different approaches for vision-based crack detection. The work by Jahanshahi et al. (2009)  
419 presents an overview of the state of the art. This is a survey of image-based techniques for defect detection on bridge  
420 structures, including crack detection techniques. In this regard, they consider two different categories: methods based  
421 on edge detection and methods based on morphological operators. Regarding edge detection, they firstly introduces  
422 methods based on the gradient of the image. Among them, the Canny operator (Canny, 1986) is one of the most used,  
423 since it provides better results in comparison with other approaches, such as Sobel or Fast-Fourier Transform (FFT)  
424 techniques (Abdel-Qader et al., 2003). By way of example, the Canny operator is used by Choi and Kim (2015) for

425 building inspection using a UAV fitted with a camera. Nevertheless, the authors of this approach indicate that there  
426 are parts of the cracks which remain undetected.

427 In the category of edge detectors, the authors of the survey also include the fast Haar transform, which performs  
428 better than the Canny operator in certain scenarios (Abdel-Qader et al., 2003), and the method by Siegel and Gunati-  
429 lake (1998). This is a multi-stage method intended for crack detection on aircraft skin using a robotic crawler. This  
430 robot is equipped with a camera and a directional light source to illuminate the inspected area. Crack detection is  
431 performed through multi-scale edge detection using a wavelet filter bank. It starts detecting rivet holes, where cracks  
432 usually appear, and defining a Region Of Interest (ROI) around them. The method detects edges at different scales  
433 using wavelets and then links them through a coarse-to-fine edge linking process. Then, it describes each edge using  
434 a feature vector containing five different features. Finally, every feature vector is classified using a Neural Network  
435 (NN) to determine whether it describes a crack or not. During tests, this detector provides a 72% of accuracy, with a  
436 27% false alarm rate.

437 The vision literature contains many other crack detectors based on edge searching. In Lim et al. (2014) approach,  
438 the authors present a wheeled robot for bridge deck crack inspection and mapping. In this approach, the edge detection  
439 consists in convolving the image with a kernel to compute the Laplacian of Gaussian (LoG). This is used to smooth  
440 the input image while computing its second derivative. Edges in the resulting image can be found looking for zero-  
441 crossings.

442 Similarly, Eschmann et al. (2012) present a edge-based crack detection method for building facade inspection  
443 using a UAV fitted with a camera. The images collected are stitched together to create a mosaic, which is later  
444 analysed searching for cracks. The crack detection method that the authors propose consists in adding Gaussian blur  
445 to the original image and then subtracting it from the image again. By doing this step, edges result almost black while  
446 the rest of the image results almost white. The authors conclude that the method needs further improvement since  
447 small cracks are not very visible after the image processing, whereas man-made edges are misclassified as cracks.

448 In Meng et al. (2015) approach, the authors propose the use of the Histogram of Oriented Gradients (HOG) for  
449 the detection of cracks in concrete surfaces such as bridges, buildings and tunnels. HOG detects edges by computing  
450 the distribution of intensity gradients of the image. Before using HOG, the original gray-scale image is binarized to  
451 generate a black and white image. Results vary depending on the threshold used during the previous binarization. The  
452 authors conclude that further work has to be done to reduce the image noise prior to using HOG.

453 Fujita and Hamamoto (2011) present a more complex method for crack detection on concrete images. The method  
454 includes two preprocessing steps (also used in Fujita et al. (2006)) and two detection steps. The first preprocessing step  
455 is a subtraction process using a median filter to remove slight variations like shadings. In the second preprocessing

456 step, a multi-scale line filter based on the Hessian matrix is used both to emphasize cracks against stains and to adapt  
457 the variation of cracks width. The first detection stage makes use of probabilistic relaxation to detect cracks coarsely  
458 and to prevent noise. Finally, a locally adaptive thresholding is performed for a finer detection. The complete method  
459 attains an Area Under the Curve (AUC) (Fawcett, 2006) of 0.98, which is very close to 1, what indicates a very  
460 successful detection rate.

461 Similar edge-based crack detection techniques are proposed by Subirats et al. (2006); Yu et al. (2007); Chambon  
462 et al. (2009). In general, edge detection techniques provide false positive detections which are produced by the  
463 presence of structural member edges or background crack-like objects. In order to minimize them, different filters are  
464 used before or after performing the edge detection.

465 Regarding the use of morphological operators, the survey by Jahanshahi et al. (2009) reviews the different basic  
466 operators (dilation, erosion, morphological gradient, opening and closing) to end up with two combinations of the  
467 opening and closing operators which allow the detection of bright and dark defects, respectively. Nieniewski et al.  
468 (1999) make use of these operators to successfully detect cracks in ferrites. A similar operator is proposed by Zhang  
469 et al. (2014), which presents a method intended for the subway tunnel safety monitoring. This method starts smooth-  
470 ing the gray-scale input image using an average filter. Then all crack-like structures are detected by means of a  
471 morphological operator. Next, the method performs image segmentation employing a thresholding operation and a  
472 second morphological operator, which is used to filter out the irrelevant noise. In order to remove the remaining large  
473 regional irrelevant objects which are still preserved as cracks, a supervised classification stage is performed. It makes  
474 use of three different features: the standard deviation of shape distance histogram, the number of pixels and the aver-  
475 age gray level. The classification is performed using an Extreme Learning Machine (Huang et al., 2012). This method  
476 is selected in this approach because of its universal approximation and classification capabilities. The complete crack  
477 detector presents an accuracy above 91%.

478 Other approaches using morphological operators are proposed by Tanaka and Uematsu (1998); Zheng et al. (2002);  
479 Yoshioka and Omatu (2009). In comparison with edge detection techniques, morphological operators do not extract  
480 all the edges in the image, which result in less false positive detections. In general, they also generate less noise.  
481 Nevertheless, morphological operators require finding the appropriate size and shape of the structuring element to  
482 obtain the best detection results.

483 Apart from the methods based on edge detection/morphological operators, the related literature contains other  
484 approaches for detecting cracks in images. Thresholding is a commonly used technique in this field. By way of  
485 example, the method presented by Cho et al. (1998) starts with two thresholding stages to separate cracks from the  
486 background in concrete surfaces. The first thresholding is used to discard clearly non-cracked areas, while the second

487 one tries to find the threshold that maximizes the quotient between the inter-class variance and the inner-class variance,  
488 being *crack* and *background* the two classes. This process is followed by a thinning procedure to reduce the crack  
489 width to 1 pixel. The remaining pixels are labelled to determine the crack morphology and length. The crack thickness  
490 is determined as the number of pixels omitted during the thinning process, while the direction of the crack (regarding  
491 the horizontal axis) is computed using a histogram of the directions of the different segments that shapes the crack.  
492 A similar procedure can be also performed to compute the thickness of a crack from the thickness of its different  
493 segments.

494 Another methodology for crack detection consists in employing region growing procedures. Yamaguchi and  
495 Hashimoto (2006, 2010) present a crack detection method for concrete surface images using percolation. This is  
496 a region-growing procedure based on the natural phenomenon of liquid permeation. The process starts from every  
497 pixel (seed pixel) in the image and grows through the darkest neighbouring pixels. The percolation proceeds until  
498 reaching a certain initial boundary. Then, the elongation of the percolated area is checked to show whether this is  
499 a potential crack (cracks are supposed to be elongated). In that case, the percolation process proceeds iteratively  
500 increasing the current boundary and checking the new elongation. Finally, when a previously defined final boundary  
501 is reached, the elongation of the percolated area is checked one last time and the seed pixel is accordingly labelled as  
502 crack or background. This method improves the classification results achieved by a conventional method that includes  
503 wavelet transform and shading correction. Nevertheless, notice that this method uses all the image pixels as seed  
504 points for percolation, so that most of the computation time is used to perform percolations starting from background  
505 pixels, which are far more than the pixels on cracks. Moreover, since just the seed pixel is labelled at the end of each  
506 percolation, every pixel is involved in many percolation processes.

507 Bonnin-Pascual (2010) improved the method by Yamaguchi and Hashimoto (2006) to deal with the two afore-  
508 mentioned issues (see also Eich et al. (2014)). In this approach, percolation processes are started only from pixels  
509 belonging to an edge (the Canny operator is used for edge computation) which besides are dark. Then, the entire  
510 area percolated is labelled as crack/background if its average grey-level value is below a certain threshold. As far as  
511 we know, this is the first method intended to deal with cracks observed in vessel metallic structures, which typically  
512 exhibit different size and elongation in comparison with cracks observed in concrete surfaces. Indeed, the authors  
513 also propose to improve the performance of the method using a corrosion detection algorithm to guide the crack  
514 detection, after the realization that most cracks present in vessel structures appear in areas affected by corrosion. A  
515 further improvement is presented in Bonnin-Pascual (2017), where an additional step is incorporated after the perco-  
516 lation process to merge different suspicious areas (i.e. potential cracks) into larger entities which are the ones finally  
517 evaluated and classified.

518 Similarly, Qu et al. (2015) improved the original method by Yamaguchi and Hashimoto (2006) adding some ad-  
519 ditional rules and checks which allow, after every percolation, labelling the entire area as crack/background. The  
520 improved method also includes a denoising algorithm, based on percolation as well, to remove the false positive de-  
521 tections. Regarding the original method, these improvements reduce considerably the processing time while increase  
522 the classification performance.

523 A different approach is presented by Sorncharean and Phiphobmongkol (2008). It consists in a method for crack  
524 detection on asphalt images based on grid cell analysis. The method is devised to deal with the problems of shading  
525 (or non-uniform illumination) and strong textures in the images. It consists in dividing the image in cells which are  
526 classified as crack or not. A cell is considered a crack if there are two (and just two) pixels of its border which are  
527 considerably darker than the others. These two pixels might be the entry and exit points of a crack in the cell. After  
528 the first classification, the original image is divided again in overlapping areas and a second classification stage is  
529 performed, in order to detect those cracks that coincide with a cell border in the first stage. Finally, a cracked cell  
530 verification stage is used to remove false positives caused by strong textures. This consists in checking whether there  
531 are dark pixels arranged in a line between the two dark border pixels. The authors report a 13% and 21% of false  
532 positive and false negative respectively.

533 Avril et al. (2004) present a crack detection approach based on the principle of the grid method. This method  
534 consists in fixing a bidirectional periodical pattern onto the inspected surface and analyzing the phase modulation  
535 induced by the crack. The Windowed Discrete Fourier Transform (WDFT) is used for detecting the phase of the  
536 image with the superimposed pattern. After removing high-frequency variations which result from electronic noise,  
537 the discontinuous variations indicate the presence of a crack. Small cracks ( $5 \mu\text{m}$  wide) are successfully detected on  
538 reinforced concrete beams using this approach. Their localization accuracy is 1.2 mm, while their opening is measured  
539 with a precision of  $1 \mu\text{m}$ . Notice that this approach requires very close-up and controlled capture of images.

540 Convolutional Neural Networks (CNN) have also been applied to the crack detection problem. Oullette et al.  
541 (2004) employ a genetic algorithm to train the weights of a CNN in order to pass through local minima, achieving  
542 an average success rate above 90%. Another related approach is proposed by Zhang et al. (2016), which compares  
543 the classification performances of a CNN, a Support Vector Machine (SVM) and a Boosting method (Freund and  
544 Schapire, 1999). The best classification ratios are attained using the CNN.

545 The use of clustering techniques for small crack detection is proposed by Zhao et al. (2015). After an initial  
546 thresholding, this method assigns the remaining pixels to clusters of cracks or clusters of background. Then, the  
547 method filters crack clusters according to their elongated shapes. The proposed clustering method is aware of whether  
548 a point lies in the extension line of an elongated cluster or on one side of it, so that the process can cover the points of

549 another crack fragment separated by a gap while keeping noise points outside.

550 Notice that the appearance of a crack (length, depth, shape, etc.) can be very different from one surface or  
551 material to another. For example, a crack that can be found inside a building after suffering an earthquake is very  
552 different to the micro-fissures that sometimes arise in an aircraft wing. Furthermore, the control of the camera-surface  
553 distance is crucial to know how big the cracks will appear in the images and, therefore, how to configure the algorithm  
554 parameters. In this regard, and unlike previous mentioned methods, Jahanshahi et al. (2013) deal with the unknown-  
555 distance problem presenting a crack detection and quantification method based on depth perception. The drawback  
556 of this approach is the need of several pictures of the scene captured from different views. These pictures are used to  
557 solve a Structure from Motion (SfM) problem (Snavely, 2008). This procedure provides the structure of the scene as  
558 well as the camera's position, orientation and internal parameters for each view. Using the depth perception provided  
559 by this 3D reconstruction (i.e. the object-camera distance), a morphological operator is then configured for crack  
560 segmentation, also considering the desired crack thickness and the camera parameters. Appropriate features are the  
561 extracted from each segmented pattern and used to finally classify real cracks. The performance of a NN, a SVM and  
562 a nearest-neighbour classifier are discussed by the authors.

563 Finally, cracks can be considered as anomalies which catch the attention of the inspector when they are present in a  
564 more or less regular surface. This approach is proposed by Bonnin-Pascual and Ortiz (2014a), whose method focuses  
565 on the idea of saliency and treats cracks as generic defects, what makes this method also applicable to detect other kind  
566 of defective situations such as corrosion and/or coating breakdown. The method makes use of a Bayesian framework  
567 to derive saliency measures based on natural statistics, combining contrast and symmetry information. These are two  
568 visual features commonly used to predict human eye fixations in images. After performing a training stage where the  
569 underlying Probability Density Functions (PDF) are estimated, the framework allows combining both bottom-up and  
570 top-down saliency, and the best results are obtained when both contrast and symmetry are employed. These features  
571 are also used in Bonnin-Pascual and Ortiz (2018) where a multi-stage generic framework for combining different  
572 visual features for the detection of defective situations, including cracks, is described. Unlike the previous Bayesian  
573 framework, the latter approach does not require a previous learning stage, though it is able to attain similar detection  
574 ratios. Both frameworks are more deeply evaluated and compared in Bonnin-Pascual (2017).

### 575 *3.2. Algorithms for Corrosion Detection*

576 Unlike the case of cracks, the computer vision literature contains just a few contributions for corrosion detection  
577 algorithms. Two main features are typically employed for corrosion detection, namely texture and colour. Texture  
578 descriptors appear in most of the approaches to characterize the roughness of corroded surfaces, while colour-based  
579 descriptors are also very popular since corrosion typically presents colours ranging from yellow to red.

580 Some approaches make use of wavelet analysis to describe the texture of corroded areas. A first example is pro-  
581 posed by Siegel and Gunatilake (1998). This approach has been already introduced in the previous section since it  
582 describes a robotic device used for aircraft skin inspection, including both crack and corrosion detection. Regard-  
583 ing corrosion, this is detected using the Discrete Wavelet Transform (DWT), which provides a characterization of  
584 the image texture at multiple resolutions and orientations. Firstly, a three-level wavelet decomposition is performed,  
585 resulting in 10 sub-bands. In a second stage, the image is divided into non-overlapping patches and 10-dimensional  
586 feature vectors are computed to describe them. The components of the feature vectors are the energy of the corre-  
587 sponding patch in each of the wavelet transform frames. Finally, each patch is classified as *corrosion* or *corrosion-free*  
588 by means of a supervised classification module. To perform the learning stage, a clustering algorithm is used to find  
589 the prototype vectors for each class. The classification stage is performed using a nearest-neighbour method. The  
590 trained algorithm is able to detect 95% of the corrosion vectors of the test set.

591 Ghanta et al. (2011) present a similar approach. In this case, the Haar wavelet is used to obtain texture information  
592 from the three planes of RGB (Red-Green-Blue) images. In more detail, each image patch is described using a  
593 feature vector which contains the energy and entropy values for the different sub-bands and colour channels. The  
594 average luminance of the patch is also added to the feature vector, which results with 25 components. Then, Principal  
595 Component Analysis (PCA, see Jolliffe (2002)) is used to reduce the dimensionality of the feature vectors to five  
596 components. To classify these vectors as *rust/non-rust*, a training stage is performed using the Least Mean Square  
597 (LMS) method.

598 Similarly, Jahanshahi and Masri (2013) evaluate the effect of using different colour spaces, colour channels and  
599 image patch sizes in a colour wavelet-based texture analysis algorithm for detecting corrosion. Like in the method  
600 by Siegel and Gunatilake (1998), this approach makes use of the DWT to obtain the coefficients that are then em-  
601 ployed to compute the energy of each image patch. Nevertheless, in the method by Jahanshahi and Masri (2013),  
602 this process is applied to the colour channels of the image. Six different colour channel combinations are consid-  
603 ered: YCbCr, CbCr, YIQ, IQ, HSI and HS. Notice that CbCr, IQ, and HS combinations result from ignoring the  
604 brightness/luminance channel of YCbCr, YIQ and HSI respectively. An Shallow Neural Network (SNN) is trained  
605 for the different combinations and considering 10 different patch sizes. The results show that the performance of the  
606 detection system improves when the features obtained from the brightness channel are excluded. The colour channel  
607 combination which provides the best performance is CbCr, with an AUC of 0.94. The HSI colour space is found the  
608 less appropriate for using with the proposed wavelet analysis.

609 Despite the results presented by Jahanshahi and Masri (2013), HSI (Hue-Saturation-Intensity) and HSV (Hue-  
610 Saturation-Value) colour spaces are widely used in colour-based corrosion detectors. These are intuitive models

611 which isolate the brightness information into a single channel. As far as we know, Choi and Kim (2005) proposed the  
612 first approach using HSI colour space for describing corrosion. For this reason, it is included in this state-of-the-art  
613 review, despite the method presented is devised to operate with images captured with a microscope. This method  
614 takes 10×10 pixel patches of the different classes and then treats the histograms of each colour channel (H, S and I)  
615 as distributions of random variables. After applying the PCA and the varimax (Kaiser, 1958) approaches, the authors  
616 conclude that the mean H value, the mean S value, the median S value, the skewness of the S distribution and the skewness  
617 of the I distribution are appropriate features to be assigned to each patch for classification.

618 Bento et al. (2009) present an approach for corrosion detection using texture information extracted from the Gray  
619 Level Co-occurrence Matrix (GLCM) (Haralick et al., 1973). The GLCM is computed for image patches of both  
620 classes, i.e. *corrosion* and *non-corrosion*, and different texture descriptors are calculated: contrast, correlation, energy  
621 and homogeneity. These descriptors are used to train a Self-Organizing Map (SOM) (Kohonen, 2001) which performs  
622 a clustering process over the different samples, creating several prototypes of both classes. During the classification  
623 stage, the nearest-neighbour approach is applied. Results show that 93% of test patches are correctly classified using  
624 this method.

625 The energy measure computed from the GLCM provides information about the texture roughness, which becomes  
626 typically high in corroded surfaces. Bonnin-Pascual (2010) makes use of this idea in combination with two alternative  
627 colour-based stages to provide two different corrosion detection methods for the visual inspection of vessel metallic  
628 structures. The colour stage of the first method describes the colour of corroded surfaces using stacked histograms  
629 from the three channels of the RGB colour space. In more detail, the three histograms are computed separately for  
630 image patches of 15×15 pixels, then the histograms are downsampled to 32 levels each, and finally they are stacked  
631 together to provide a 96-component descriptor. During the learning stage, the descriptors computed from the training  
632 set are clustered using *K-means* (Theodoridis and Koutroumbas, 2006) to generate a colour descriptors dictionary for  
633 corrosion. During the classification stage, an image patch is considered to present a colour typical of corrosion if its  
634 colour descriptor is similar to at least one of the models in the dictionary, according to the Bhattacharyya distance.  
635 On the contrary, the colour stage of the second method makes use of a colour map of typical corrosion colours. This  
636 map is previously computed as a 2-dimensional histogram of hue and saturation values (from the HSV colour space)  
637 corresponding to all pixels labelled as corrosion in the training set. Different post-processing methods are proposed to  
638 fill the gaps and increase the generalization of the histogram. During the classification stage, the probability that a pixel  
639 has a colour similar to corrosion is deemed as proportional to the value of the corresponding bin in the histogram.  
640 Both corrosion detection methods provide good classification ratios but the latter is better in terms of computation  
641 time. Further evaluation and testing using other colour spaces can be found in Bonnin-Pascual (2017).



642 Similarly, Medeiros et al. (2010) present a corrosion detector which combines the texture descriptors used by Bento  
643 et al. (2009) with colour information using the HSI colour space. The colour descriptors consist in the four first  
644 statistical moments extracted from each colour channel histogram. The resulting set of descriptors (texture and colour)  
645 is optimized using PCA to eliminate redundant attributes. Finally, the classification is performed using Fisher Linear  
646 Discriminant Analysis (FLDA) (Webb and Copsey, 2011) and different subsets of descriptors. The best results are  
647 obtained using 13 features combining both texture and colour information, which provide more than 90% of accuracy.

648 Bonnin-Pascual and Ortiz (2014b) make use of a machine learning technique to learn the texture of corroded  
649 surfaces. This consists in using the *Adaptive Boosting* paradigm (AdaBoost, see Freund and Schapire (1999)) for  
650 both learning and classifying, and feeding the method with different statistical measures obtained after convolving  
651 Law's texture energy filters (Law, 1980) with patches centred at both corroded and non-corroded pixels. In this  
652 work, the implementation of AdaBoost makes use of Classification and Regression Trees (CART) as weak classifiers.  
653 This texture stage is combined with the aforementioned colour stage based on the hue-saturation histogram presented  
654 in Bonnin-Pascual (2010), leading to good classification ratios.

655 Some approaches make use of a Support Vector Machine to evaluate the corrosion degree of metallic surfaces.  
656 Yamana et al. (2005) employ a SVM to classify electric pole crossarms into categories *reuse*, *retire* or *reuse after*  
657 *plating*, depending on the colour of the rust expressed in the RGB colour space. Indeed, this approach compares the  
658 performances attained by different machine learning techniques, including a SVM, a k-Nearest Neighbour (kNN), a  
659 Radial Basis Function (RBF) network, and a Multi-Layer Perceptron (MLP); but the SVM provides the best results.  
660 The method starts reducing the image resolution from 640×480 pixels to 20×15, in order to reduce the number of  
661 features. Then, the training and classification stages make use of vectors with 20×15×3 (three colour channels)  
662 components, where each colour channel is expressed with a value ranging from 0 to 255. The resulting method  
663 provides an accuracy above 97%.

664 Tsutsumi et al. (2009) also use a SVM in their approach. It presents a system to categorize images from metallic  
665 power transmission towers depending on its deterioration degree. Three classes are defined: *early phase*, *adequate*  
666 *phase* and *late phase*. Two different methods are considered in this approach to represent the colour information  
667 which is later used to feed the SVM. The first one consists in using RGB scaling, that is, using a scaled version of the  
668 image where the colour of each pixel is computed as the average of the corresponding pixels in the original image.  
669 The second approach consists in using the concatenation of the histograms of the three channels in the HSV colour  
670 space. Both approaches are assessed using different sizes for the RGB structure or the HSV histogram. The best  
671 classification performance provided by the SVM is around 85%, and it is obtained when using an HSV histogram  
672 with 192 bins.

673 Ortiz et al. (2015) present a corrosion detector based on a Shallow Neural Network (SNN) which again combines  
674 both colour and texture information. In this approach, the authors compare the results obtained with several combi-  
675 nations of different descriptors. Regarding colour, two descriptors are evaluated: on the one hand, the average value  
676 of each channel within a neighbourhood; on the other hand, the stacked 8-bin histograms for downsampled intensity  
677 values for each channel in the same neighbourhood. Additionally, both HSV and RGB colour spaces are checked. Re-  
678 garding texture, center-surround differences are considered in two different ways: signed Surround Differences (SD)  
679 between a central pixel and its neighbourhood and 10-bin histograms of uniform Local Binary Patterns (LBP). The  
680 number of hidden neurons is also varied, resulting in a total amount of 336 different combinations. The best results  
681 are obtained for LBPs with SDs and using 8-bin histograms of hue and saturation channels. A similar approach is  
682 presented in Ortiz et al. (2016), where colour is described computing the dominant colours inside a square patch, and  
683 texture is described using a number of statistical measures about the SD computed for every colour channel.

684 A completely different solution is provided by Ji et al. (2012). They present an approach for corrosion detection  
685 based on watershed segmentation (Vincent and Soille, 1991). This method considers a gray-scale image as a 3D  
686 surface where the darkest pixels are the local minima. The segmentation process consists in placing a water source  
687 in each local minimum to flood the entire image, building barriers where different water sources meet. These barriers  
688 constitutes the watershed segmentation. This method sometimes leads to over-segmentation due to the presence of  
689 noise or weak edges in the image. The authors propose a method to prevent this problem. It consists in merging  
690 adjacent regions which present a similar average hue. The resulting segmentations look better despite quantitative  
691 results are not provided.

692 Idris et al. (2015) evaluate different pre-processing image enhancement filters in order to improve the results  
693 obtained with a corrosion detector based on the red channel histogram. The set of filters includes mean filtering,  
694 median filtering, Gaussian filtering, wavelet de-noising, Weiner filtering, Bayer filtering, and anisotropic diffusion.  
695 The authors propose using the Peak Signal-to-Noise Ratio (PSNR) to select among the different filters, so that the  
696 most suitable one is applied depending on the specific lighting conditions. The results show that the Bayer filter  
697 provides the highest PSNR value for the majority of the images.

698 Another method that does not use any machine learning process is provided by Roberts (2016). As seen in  
699 Section 2.2, this approach makes use of a UAV for corrosion detection. The detection algorithm consists in a simple  
700 method using a colour threshold in the HSV colour space. Nevertheless, the author provides only qualitative results  
701 and indicates that the use of some texture measure probably would improve the performance.

702 Recently, CNNs have also been applied to the corrosion detection problem. Petricca et al. (2016) compare a  
703 standard computer vision technique with a CNN for classifying images as *rust/non-rust*. In this approach, an image

704 showing corroded elements is considered as *rust*, despite the rest of the image is showing non-corroded elements or  
705 surfaces. The standard technique involved in the comparison consists in merely accounting for the reddish pixels of the  
706 image. The image is considered corroded if the counter exceeds 0.3% of the total number of pixels. On the other side,  
707 the CNN is implemented using a pre-trained model based on AlexNet (Krizhevsky et al., 2012). Results show that the  
708 CNN performs better in a real case scenario (78% versus 69% of accuracy). The authors further propose including  
709 the standard technique for removing false positives before executing the CNN-based method. Within the research  
710 project ROBINS, Ortiz et al. (2018) outline preliminary results regarding the use of two well-known deep learning  
711 object recognition approaches for detecting corrosion in vessel structures. The selected approaches are the Single-  
712 Shot multi-box Detector (SSD) (Liu et al., 2016) and Faster R-CNN (Ren et al., 2015), being the latter combined with  
713 VGG16 (Simonyan and Zisserman, 2014). Results indicate that Faster R-CNN behaves better in general, providing  
714 higher precision values.

715 Finally, as indicated in Section 3.1, the idea of saliency has also been applied for corrosion detection. In this re-  
716 gard, the aforementioned approaches by Bonnin-Pascual and Ortiz (2014a, 2018) also deal with corrosion, employing  
717 contrast and symmetry as features to approach the detection. The results show that saliency also allows detecting  
718 this kind of defect. Furthermore, in Bonnin-Pascual and Ortiz (2017), a saliency-based method is used to improve  
719 the performance of the corrosion detector firstly introduced in Bonnin-Pascual (2010), based on texture and colour  
720 features. In this approach, saliency is used in a previous stage to filter out non-defective areas. The results show that  
721 the saliency-based classifier allows boosting the specific defect detector (Bonnin-Pascual, 2010), reducing the false  
722 positives and increasing precision.

### 723 3.3. Discussion

724 Table 3 summarizes the approaches reviewed in Section 3.1. A wide variety of computer vision techniques specif-  
725 ically devised for crack detection have been investigated so far. It is important to notice that most of the methods  
726 are intended to detect cracks on concrete surfaces, which typically present a very narrow and elongated shape, unlike  
727 metallic cracks. Typically, these methods require from a suitable image capture procedure in order to provide good  
728 results. This includes a specific distance to the scene (typically very short) or a certain camera position regarding the  
729 inspected surface. In some approaches, lighting must also be controlled. Furthermore, most of them require from  
730 learning and/or parameter-tuning stages to attain acceptable performance.

731 Similarly, Table 4 details the main features of the different approaches for corrosion detection reviewed in Sec-  
732 tion 3.2. Almost all the existing approaches rely on colour and/or texture features, which are usually learned using  
733 some machine learning technique. This implies that a dataset is needed for the training stage or to seek for the  
734 appropriate configuration that provides a good detection performance.

735 The idea of using saliency for crack and corrosion detection is exploited by part of these approaches, which  
736 allows considering these two (and even other) defective situations together. The latest approaches in these line offer  
737 the advantage that they do not require a previous training or parameter-tuning stage, while they are able to perform  
738 well in datasets containing images from vessel structures captured under different illumination conditions and from  
739 different distances. These techniques are also useful to be executed as a first stage to filter out non-defective situations,  
740 prior to executing specific methods for detecting the aforementioned kinds of defects.

741 Finally, the boom of deep learning techniques is also noticeable in both crack and corrosion detection fields,  
742 dominating some of the most recent approaches. Unlike the rest of the surveyed methods, these contributions usually  
743 do not need a deep study about the features that allow a better description of the defect, since these features naturally  
744 come up during the training stage, once the weights of the CNN are available. The main drawback of these approaches  
745 is the need of a very large dataset and a GPU for a proper training.

#### 746 **4. Conclusions**

747 This paper reviews a number of contributions from fields related to the robotization of ship inspection. In the first  
748 part, we differentiate between robotic platforms for underwater inspection and those intended for inspecting above  
749 the water line (actually, these platforms can be used to inspect the entire vessel hull if this is situated in a dry-dock).  
750 Regarding underwater platforms, the most recent approaches focus on the use of free-floating AUVs equipped with  
751 cameras and sonar devices, what indicates that it is not necessary to be attached to the vessel structure to perform a  
752 proper visual inspection (keep at a short distance is enough). A similar situation occurs with the above-water plat-  
753 forms. Regarding non-marine robots, one can find a number of robotic crawlers capable of carrying different payloads  
754 (e.g. arms with Ultrasound Thickness Measurement (UTM) devices), although flying devices have proved to be able  
755 to reach target areas more quickly and directly, and provide a wider view of the inspected surface. Consequently,  
756 the robotics literature comprises a large number of approaches –most of them proposed in the recent years– which  
757 describe aerial devices for the inspection of different kinds of infrastructures, hence being potentially usable for vessel  
758 hull inspection. Having in mind the idea of providing the vessel surveyors with a “flying camera”, the paradigm of  
759 supervised autonomy has proved to result into a good option in several studies.

760 Once the agents in charge of collecting inspection data have been reviewed, in the second half of this paper we  
761 consider a number of contributions focused on detecting the main defective situations which affect vessel metallic  
762 structures, i.e. cracks and corrosion. Regarding cracks, the related literature comprehends a diversity of detection  
763 methods, most of which make use of an edge detection technique or involve morphological operators. Another  
764 point in common among many of the existing approaches is that they are intended for the detection of cracks on

Table 3: Representative vision-based crack detection approaches.

<b>Approach</b>	<b>Particular technique</b>	<b>Reference</b>	
Edge detection	Canny	Choi and Kim (2015)	
	LoG	Lim et al. (2014)	
	LoG + labelling + Dijkstra	Yu et al. (2007)	
	Wavelets	Siegel and Gunatilake (1998)*, Subirats et al. (2006), Chambon et al. (2009)	
	HOG	Meng et al. (2015)	
	Image differencing	Eschmann et al. (2012)	
	Image differencing + Hessian analysis	Fujita et al. (2006)	
	Image differencing + Hessian analysis + probabilistic relaxation	Fujita and Hamamoto (2011)	
	Morphological operators		Tanaka and Uematsu (1998), Nieniewski et al. (1999), Zheng et al. (2002), Yoshioka and Omatsu (2009), Jahanshahi et al. (2013)*, Zhang et al. (2014)*
		Region growing	Yamaguchi and Hashimoto (2006, 2010), Bonnin-Pascual (2010, 2017) Eich et al. (2014); Qu et al. (2015)
Thresholding + thinning + labelling		Cho et al. (1998)	
Grid cell analysis		Sorncharean and Phiphobmongkol (2008)	
Grid method (WDFT)		Avril et al. (2004)	
CNN		Oullette et al. (2004)*, Zhang et al. (2016)*	
Clustering		Zhao et al. (2015)	
Saliency		Bonnin-Pascual and Ortiz (2014a)*, Bonnin-Pascual and Ortiz (2018), Bonnin-Pascual (2017)	
Other			

\* indicates that some machine learning technique is involved.

Table 4: Representative vision-based corrosion detection approaches.

Method	Reference	Attributes	Learning	Classification	
Using wavelets	Siegel and Gunatilake (1998)	Energy	Clustering	Nearest-neighbour	
	Ghanta et al. (2011)	Energy and entropy in colour + mean intensity*		LMS	
Using GLCM	Jahanshahi and Masri (2013)	Energy in colour		SNN	
	Choi and Kim (2005)	Metrics from HSI hist, GLCM and morphology*	Clustering	Nearest-neighbour	
	Bento et al. (2009)	Contrast, correlation, energy and homogeneity	SOM	Nearest-neighbour	
	Bonnin-Pascual (2010)	RGB stacked hist / HS histogram	Clustering / Colour map	Distance threshold / Map query	
Machine Learning	Medeiros et al. (2010)	Contrast, correlation, energy and homogeneity and HSI hist moments*		FLDA	
	Bonnin-Pascual and Ortiz (2014b)	Statistical measures from convolutions	AdaBoost with CARTs		
Using saliency	Bonnin-Pascual and Ortiz (2014a)	Contrast and symmetry	PDF estimation		
		RGB channels		SVM	
	Yamana et al. (2005)	RGB channels / HSV stacked histograms		SVM	
		Tsutsumi et al. (2009)	HSV stacked histograms		SVM
	Other	Ortiz et al. (2015)	Mean colour / stacked histograms + SD / LBP		SNN
			Dominant colours, measures from SD		SNN
		Ortiz et al. (2016)	HSV channels		CNN
WS segmentation + mean hue	Ortiz et al. (2018)	RGB channels		CNN	
		Ji et al. (2012)			
Red channels hist	Idris et al. (2015)				
Threshold in HSV	Roberts (2016)				
Threshold in saliency	Bonnin-Pascual and Ortiz (2016, 2018)				

**Attributes:** attributes used in machine learning techniques. \* indicates that PCA is applied. hist/histogram

765 concrete surfaces, which typically present a different width and elongation in comparison to the cracks that occur in  
766 the metallic structures of vessels. Regarding corrosion, colour and texture are the two main features employed by the  
767 existing detection methods. Most of them rely on some machine learning technique to learn how corrosion looks like,  
768 which requires an image dataset for training. A special mention must be made to deep learning methods, which are  
769 being used in demanding object recognition and classification tasks, including the detection of cracks and corrosion.  
770 Generic defect detectors based on saliency must also be kept in mind due to their good detection performance and  
771 their usefulness as a previous filter to reduce the false positives of detection algorithms designed for specific defects.

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