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

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

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

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

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

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

To perform a complete hull inspection, the vessel has to be emptied and situated in a dockyard (and probably in a
dry-dock), where typically temporary staging, lifts, movable platforms, etc. need to be installed to allow the workers
for close-up inspection of all the different metallic surfaces and structures. The items to survey depend on the type
and age of the vessel, as well as the kind of survey that is being carried out. To illustrate the enormity of the inspection
task, the surveying of a central cargo tank on a Very Large Crude Carrier (VLCC) can involve checking over 860 m
of web frames (primary stiffening members) and approximately 3.2 km of longitudinal stiffeners, while the complete
survey to verify the state of the whole vessel can mean the visual assessment of more than 600,000 m² of steel.

Furthermore, the surveys are on many occasions performed in a potentially hazardous environment with both
flammable and toxic gases and significant heights involved. As a result, although accidents are extremely rare, when
they do arise they can have serious consequences. Due to these complications, the total cost of a single surveying
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give rise to a very significant amount once you factor in the vessel’s preparation, use of yard’s facilities, cleaning,
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ventilation, and provision of access arrangements. In addition, the owners may experience significant lost opportunity
costs while the ship is inoperable.
Infrastructure inspection by means of robots is a line of research that the EU has been lately supporting through the
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FP7 and H2020 programmes (projects MINOAS [Eich et al. 2014], INCASS [Ortiz et al. 2017] and ROBINS [Ortiz
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et al. 2018], among others) and through specific calls, such as Robotics in Application Areas: b) Innovation Actions
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- Robotics for infrastructure inspection and maintenance, ICT-09-2019-2020 (European Commission 2017).
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Focusing on the particular case of vessel inspection, this paper reviews technological advances which (at least
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potentially) can facilitate such processes. To be precise, this survey reviews contributions on two key fields. Firstly,
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Section 2 reviews approaches related to robotic platforms suitable for vessel hull inspection, irrespectively of the
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mechanical structure of the device and its locomotion approach (e.g. magnetic crawlers, free-floating vehicles, aerial
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platforms, etc). Next, the survey focus on processing the data collected by the robots, particularly as regards defect
detection by visual means. To be more precise, in Section 3 we overview vision-based detection algorithms for the
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two aforementioned kinds of defects, i.e. cracks and corrosion. Both sections finalize discussing about the current
trends in these specific research fields. Finally, Section 4 reaches some conclusions on the topics surveyed.

2. Robotic Platforms for Inspection

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

2.1. Robotic Platforms devised for Vessel Hull Inspection

The robotics literature contains several contributions about robots for vessel inspection. Most of them consist in
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underwater vehicles for the inspection of the submerged part of the vessel hull. As a first example, the vehicle pre-
sented by Lynn and Bohlander (1999) is an underwater Remotely Operated Vehicle (ROV) intended for inspection. This is a free-floating vehicle which is able to take paint-thickness measurements of the underwater hull using a specific probe. The Little Benthic Crawler (Newsome and Rodocker 2009) is another remotely operated robot equipped with a camera suitable for vessel visual inspection. This is a commercial 2-piece robot consisting of a 5-thruster ROV and a removable 4-wheel drive crawler skid assembly. The latter houses a vortex generator which provides attractive force on any relatively flat surface. Another example is authored by Ishizu et al. (2012), who present the design and development of a mechanical contact mechanism that allows an ROV to keep a suitable position and orientation to improve the visual inspection of the hull.

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

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

The HROV (Hybrid-ROV) (Ferreira et al. 2013) is an underwater hull-crawling vehicle devised for the ultrasonic inspection of Floating, Production, Storage and Offloading (FPSO) units. Like the Lamp Ray, the HROV can also
be operated in free-flying mode to reach the hull surface, and then attach itself using the vertical thrusters. For
the displacement over the hull surface, it makes use of two motorized tracks. Its sensor suite includes an altimeter
to measure the distance to the hull, a depthmeter, an Inertial Measurement Unit (IMU) providing acceleration and
attitude information, and a Doppler Velocity Log (DVL) which provides the hull-relative velocity and position (i.e.
dead-reckoning via integration).

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

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

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

The *HAUV* is used again by *(Walter et al., 2008)*. In this approach, the *DIDSON* sonar is integrated in a Simultane-
ous Localization and Mapping (SLAM) framework. The latter technique consists in creating an incremental map of an
unknown environment while localizing the robot within this map *(Durrant-Whyte and Bailey, 2006)*. Similarly, *(Walter
et al., 2008)* perform SLAM using an Exactly Sparse Extended Information Filter (ESEIF). This approach needs a
manual selection of feature correspondence in the sonar image due to the device’s low resolution and low signal-to-
noise ratio, in comparison with images taken using optical cameras.
VanMiddlesworth et al. (2013) present another SLAM-based approach using the HAUV and the DIDSON sonar. This approach consists in aligning point clouds gathered over a short time scale using the Iterative Closest Point (ICP) algorithm. To improve the alignment, the authors present a system for smoothing these “submaps” and removing outliers. Constraints from submap alignment are integrated into a 6-Degrees of Freedom (DOF) pose graph, which is optimized to estimate the full vehicle trajectory over the duration of the inspection task.

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

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

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

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

Kim and Eustice (2013) improve the vision-based pose-graph SLAM method presented some years before (Kim and Eustice 2009). They introduce an online Bag-of-Words (BoW) measure for intra and inter-image saliency in order to identify informative key-frames. Ozog et al. (2016) use a similar technique in underwater saliency-informed SLAM to relocate the HAUV in a multiple session hull inspection. Using this approach, a single-session SLAM result is initially used as a prior map for later sessions, while the robot automatically merges the multiple surveys into a common hull-relative reference frame. To perform the relocalization step, the authors use a particle filter to leverage the locally planar representation of the ship hull surface. Furthermore, Generic Linear Constraints (GLC) allow
managing the computational complexity of the SLAM system as the robot accumulates information across multiple
sessions. The authors provide results for 20 SLAM survey sessions for two large vessels over the course of days,
months, and even up to three years.

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

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

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

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

2.2. Aerial Robotic Platforms for Inspection

The civilian use of Unmanned Aerial Vehicles (UAV) for removing personnel from hazardous situations has grown
significantly in recent years. One particular sector of application is visual inspection. Among the different aerial
platform configurations, the Small Unmanned Aerial Systems (SUAS) with capabilities for Vertical Take-Off and
Landing (VTOL), such as the multicopters (in the form of quadrotors, hexarotors, octorotors, etc), ducted-fans or
coaXial rotor-based helicopters, are the most used platforms. These platforms, sometimes called Micro-Aerial Vehicles
(MAV), present high maneuverability and are able to operate in confined spaces, including indoor environments. These
platforms are typically characterized by a limited payload and autonomy, as well as by small size and reduced cost.
The article by Huerzeler et al. (2012) presents some scenarios for industrial and generic visual inspection using aerial vehicles, while the platform requirements are discussed as well. Additionally, Morgenthal and Hallermann (2014) provide further analysis about UAV properties for visual inspection, focusing on the prevention of image degradation due to the vehicle movement.

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

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

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

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

A widely used sensor is the Light Detection and Ranging (LiDAR) device, also known as laser scanner. The use of this sensor, inherited from ground robotics, allows MAVs for positioning (and sometimes mapping), while a camera is typically used for the inspection task. In combination with GPS and IMU data, Serrano (2011) proposes using LiDAR data for culvert inspection using a MAV. The idea is to operate the robot outdoors, taking off from a military vehicle, and positioning the MAV in front of the culvert entrance, making an intensive use of GPS data. To
perform the inspection inside the culvert, where GPS signal is probably not received, the system estimates the MAV
state combining the data provided by the LiDAR sensor with IMU and GPS data within an EKF. Then, the operator
can use a Pan-Tilt-Zoom (PTZ) camera to perform the inspection.

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

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

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

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

While the experiments presented in this paper are performed in a mock environment, Nikolic et al. (2013) show some
results obtained inspecting a boiler system with a more evolved version of the visual-inertial sensor.

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

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

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

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

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

Katrašnik et al. (2010) present a survey of mobile robots for distribution power line inspection. It includes dif-
ferent computer vision techniques used on-board UAVs for camera stabilization, pole tracking and automated defect
detection. Regarding UAV configuration, two different approaches are reviewed. The first one consists in a ducted-fan
rotorcraft (Jones [2005]) which is able to estimate its position and attitude from an image of three conductors of the
power transmission line using the Hough transform. The second reviewed approach consists in an autonomous heli-
copter (Campoy et al., 2001) which is able to fly along power line using a vector-gradient Hough transform for cable
detection and stereo vision for determining the position of the cable relative to the helicopter.

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

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

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

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

Also related with contact-based inspection, Cacace et al. (2015) propose a high-level control system to allow a
UAV to autonomously perform complex tasks in close and physical interaction with the environment. This system
combines hierarchical task decomposition, mixed-initiative control and path planning techniques to allow reactivity and sliding autonomy. The approach is evaluated in a physical inspection task and in a visual inspection task, both performed under laboratory conditions.

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

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

The same authors describe a different approach as part of the research performed within the project INCASS (Ortiz et al., 2017). This is based on the use of the Supervised Autonomy paradigm, which allows the user/pilot to concentrate on the task at hand, issuing displacement commands using a gamepad or a joystick, while the platform is in charge of all the safety-related matters, such as obstacle avoidance. Within this framework, the control pipeline does not require from the estimation of the robot position, which may be difficult to obtain accurately, but only the estimation of its velocity (in the three axes) and height. To estimate the vehicle speed, two optical flow sensors are employed, one looking downwards and the other looking forward, which respectively supply velocity estimations with regard to
the floor and to the inspected wall. The flight height is estimated using a laser altimeter. Furthermore, the control architecture implements a set of robotic behaviours in charge of increasing the platform autonomy during the operation (e.g. the *go-ahead* behaviour makes the vehicle track the indicated speed until an obstacle is reached or the user issues a different displacement command). It is worth mentioning that images collected using such a device are later processed searching for corrosion.

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

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

2.3. Discussion

Table 1 summarizes the main features of the robotics platforms for vessel inspection reviewed throughout Section 2.1. They are sorted by year of publication. As can be observed, recent approaches for underwater systems focus on autonomous vehicles (AUV) instead of on teleoperated platforms (ROV). The boom of vision-based perception, pushed by the high-computational capabilities of current processors and Graphical Processing Units (GPU), makes cameras the most used devices to obtain that level of automation. Data provided by these sensors is usually merged
into EKF and/or SLAM processes with data provided by other sensors typically used in underwater robotics, such as DVL or sonar. Regarding approaches for above-water inspection with crawlers, 3D position estimation becomes a hard task especially when the robotic platform traverses between plates of different orientations (wheel odometry tends to fail in such situations). For this reason, existing approaches focus on teleoperated platforms where the position estimation (if any) is used for informing the user/pilot but not for feeding a position control algorithm.

Similarly, Table 2 summarizes all the aerial platforms for inspection reviewed in Section 2.2. They are also sorted by year of publication. As previously mentioned, the reviewed approaches are potentially useful for inspecting (at least certain areas of) vessels. Most contributions are from the last decade, what is probably due to the reduction in size of computation boards, which in turn has contributed to the popularization of MAVs (i.e. small-size platforms). Among the different configurations, quadcopters and hexacopters are the most used. As it happens with non-aerial platforms, the majority of the aerial approaches make use of vision systems for the state estimation, using different SLAM and/or KF approaches for computing the platform state. Such vision systems can be based on monocular cameras, stereo rigs, RGB-D cameras or optical flow sensors. Another sensor which is highly used in aerial robotics is the LiDAR. This results useful in dark environments where vision systems may fail, though typically require higher payload capabilities. Several of the different approaches combine the data provided by the selected main sensor with 3-axis motion data supplied by an IMU (i.e. linear accelerations and orientation) to improve the platform state estimation.

Regarding the autonomy level, some approaches focus on fully autonomous aerial platforms while other tackle the idea of shared or supervised autonomy. This last operating paradigm allows the human/inspector to interactively 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 |
|----------------------------------------|---------------|--------------|------------------------|
| 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                  |
| Akinliev et al. (2008)                 | AURORA        | AUV ⊗        | opt odo/LBL US/cam      |
| Menegaldo et al. (2008)                | SIRUS         | ROV1 ⊙      | 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 link US    |
| Newsome and Rodocker (2009)            | LBC           | ROV ⊙/≈      | —                      |
| Packard et al. (2010)                  | REMUS         | AUV ≈        | DVL+IMU +depth sonar    |
| Eich and Vögele (2011)                 | MIRA          | ROV1 ⊗      | 3D tracker cam          |
| Fondahl et al. (2012), Ahmed et al. (2015) | —             | —            | —                      |
| Schattschneider et al. (2011)          | —             | —            | EKF SLAM: stereo        |
| Bibuli et al. (2012)                   | MARC          | ROV1 ⊗      | —                      |
| Hover et al. (2012)                    | HAUUV         | AUV ≈        | SLAM: DVL +sonar+cam sonar/cam |
| Ishizu et al. (2012)                   | LBV150*       | ROV Δ/≈      | —                      |
| Ferreira et al. (2013)                 | HROV          | AUV Δ/≈      | depth+alt +IMU+DVL US   |
| Kim and Eustice (2013)                 | HAUUV         | AUV ≈        | SLAM: cam sonar/cam     |
| VanMiddlesworth et al. (2013)          | HAUUV         | AUV ≈        | SLAM: sonar sonar       |
| Ozog and Eustice (2015)                | HAUUV         | AUV ≈        | SLAM: stereo +DVL sonar/cam |
| Ozog et al. (2016)                     | HAUUV         | AUV ≈        | SLAM: cam sonar/cam     |

**Name:** * indicates a commercial robot used for testing.  
**Vehicle type:** ⊙/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                     |
| Eschmann 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                     |
| Sampredo et al. (2014)       | Power tower    | —             | —                   | img+tower               |
| Martinez et al. (2014)       | Power tower    | —             | —                   | img+tower               |
| Quater et al. (2014)         | Photovoltaic 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                     |
| Mathé and Bušoniu (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) | Vessel str.    | 4C/6C         | opt flow            | img+corrosion           |
| Ortiz et al. (2015)          | Metallic str.  | 4C            | —                   | img+corrosion           |
| Roberts (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)| Vessel str.  | 4C/6C         | KF: opt flow + LiDAR+IMU | img+defects           |
| Bonnin-Pascual et al. (2019) | Vessel str.    | 4C/6C         | Part. filter: RGB-D vis odo+IMU | thermal +fire       |
| Fang et al. (2017)           | Shipboard env. | 4C            | —                   |                         |

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.
3. Vision-based Defect Detection Algorithms

Visual inspection is one of the predominant methods used in quality/integrity assessment procedures. It is a subjective process that relies on an inspector’s experience and mental focus, making it highly prone to human error.

The development of automated inspection technology can overcome these shortcomings.

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

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

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

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

3.1. Algorithms for Crack Detection

This section reviews different approaches for vision-based crack detection. The work by Jahanshahi et al. (2009) presents an overview of the state of the art. This is a survey of image-based techniques for defect detection on bridge structures, including crack detection techniques. In this regard, they consider two different categories: methods based on edge detection and methods based on morphological operators. Regarding edge detection, they firstly introduces methods based on the gradient of the image. Among them, the Canny operator (Canny 1986) is one of the most used, since it provides better results in comparison with other approaches, such as Sobel or Fast-Fourier Transform (FFT) techniques (Abdel-Qader et al. 2003). By way of example, the Canny operator is used by Choi and Kim (2015) for
building inspection using a UAV fitted with a camera. Nevertheless, the authors of this approach indicate that there are parts of the cracks which remain undetected.

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

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

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

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

Fujita and Hamamoto (2011) present a more complex method for crack detection on concrete images. The method includes two preprocessing steps (also used in Fujita et al. (2006) and two detection steps. The first preprocessing step is a subtraction process using a median filter to remove slight variations like shadings. In the second preprocessing
step, a multi-scale line filter based on the Hessian matrix is used both to emphasize cracks against stains and to adapt the variation of cracks width. The first detection stage makes use of probabilistic relaxation to detect cracks coarsely and to prevent noise. Finally, a locally adaptive thresholding is performed for a finer detection. The complete method attains an Area Under the Curve (AUC) \textit{(Fawcett, 2006)} of 0.98, which is very close to 1, what indicates a very successful detection rate.

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

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

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

Apart from the methods based on edge detection/morphological operators, the related literature contains other approaches for detecting cracks in images. Thresholding is a commonly used technique in this field. By way of example, the method presented by Cho et al. (1998) starts with two thresholding stages to separate cracks from the background in concrete surfaces. The first thresholding is used to discard clearly non-cracked areas, while the second
one tries to find the threshold that maximizes the quotient between the inter-class variance and the inner-class variance, being crack and background the two classes. This process is followed by a thinning procedure to reduce the crack width to 1 pixel. The remaining pixels are labelled to determine the crack morphology and length. The crack thickness is determined as the number of pixels omitted during the thinning process, while the direction of the crack (regarding the horizontal axis) is computed using a histogram of the directions of the different segments that shapes the crack. A similar procedure can be also performed to compute the thickness of a crack from the thickness of its different segments.

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

Bonnin-Pascual (2010) improved the method by Yamaguchi and Hashimoto (2006) to deal with the two aforementioned issues (see also Eich et al. (2014)). In this approach, percolation processes are started only from pixels belonging to an edge (the Canny operator is used for edge computation) which besides are dark. Then, the entire area percolated is labelled as crack/background if its average grey-level value is below a certain threshold. As far as we know, this is the first method intended to deal with cracks observed in vessel metallic structures, which typically exhibit different size and elongation in comparison with cracks observed in concrete surfaces. Indeed, the authors also propose to improve the performance of the method using a corrosion detection algorithm to guide the crack detection, after the realization that most cracks present in vessel structures appear in areas affected by corrosion. A further improvement is presented in Bonnin-Pascual (2017), where an additional step is incorporated after the percolation process to merge different suspicious areas (i.e. potential cracks) into larger entities which are the ones finally evaluated and classified.
Similarly, Qu et al. (2015) improved the original method by Yamaguchi and Hashimoto (2006) adding some additional rules and checks which allow, after every percolation, labelling the entire area as crack/background. The improved method also includes a denoising algorithm, based on percolation as well, to remove the false positive detections. Regarding the original method, these improvements reduce considerably the processing time while increase the classification performance.

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

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

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

The use of clustering techniques for small crack detection is proposed by Zhao et al. (2015). After an initial thresholding, this method assigns the remaining pixels to clusters of cracks or clusters of background. Then, the method filters crack clusters according to their elongated shapes. The proposed clustering method is aware of whether 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
another crack fragment separated by a gap while keeping noise points outside.

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

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

3.2. Algorithms for Corrosion Detection

Unlike the case of cracks, the computer vision literature contains just a few contributions for corrosion detection algorithms. Two main features are typically employed for corrosion detection, namely texture and colour. Texture descriptors appear in most of the approaches to characterize the roughness of corroded surfaces, while colour-based descriptors are also very popular since corrosion typically presents colours ranging from yellow to red.
Some approaches make use of wavelet analysis to describe the texture of corroded areas. A first example is proposed by Siegel and Gunatilake (1998). This approach has been already introduced in the previous section since it describes a robotic device used for aircraft skin inspection, including both crack and corrosion detection. Regarding corrosion, this is detected using the Discrete Wavelet Transform (DWT), which provides a characterization of the image texture at multiple resolutions and orientations. Firstly, a three-level wavelet decomposition is performed, resulting in 10 sub-bands. In a second stage, the image is divided into non-overlapping patches and 10-dimensional feature vectors are computed to describe them. The components of the feature vectors are the energy of the corresponding patch in each of the wavelet transform frames. Finally, each patch is classified as corrosion or corrosion-free by means of a supervised classification module. To perform the learning stage, a clustering algorithm is used to find the prototype vectors for each class. The classification stage is performed using a nearest-neighbour method. The trained algorithm is able to detect 95% of the corrosion vectors of the test set.

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

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

Despite the results presented by Jahanshahi and Masri (2013), HSI (Hue-Saturation-Intensity) and HSV (Hue-Saturation-Value) colour spaces are widely used in colour-based corrosion detectors. These are intuitive models
which isolate the brightness information into a single channel. As far as we know, Choi and Kim (2005) proposed the first approach using HSI colour space for describing corrosion. For this reason, it is included in this state-of-the-art review, despite the method presented is devised to operate with images captured with a microscope. This method takes 10×10 pixel patches of the different classes and then treats the histograms of each colour channel (H, S and I) as distributions of random variables. After applying the PCA and the varimax (Kaiser, 1958) approaches, the authors conclude that the mean H value, the mean S value, the median S value, the skews of the S distribution and the skews of the I distribution are appropriate features to be assigned to each patch for classification.

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

The energy measure computed from the GLCM provides information about the texture roughness, which becomes typically high in corroded surfaces. Bonnin-Pascual (2010) makes use of this idea in combination with two alternative colour-based stages to provide two different corrosion detection methods for the visual inspection of vessel metallic structures. The colour stage of the first method describes the colour of corroded surfaces using stacked histograms from the three channels of the RGB colour space. In more detail, the three histograms are computed separately for image patches of 15×15 pixels, then the histograms are downsampled to 32 levels each, and finally they are stacked together to provide a 96-component descriptor. During the learning stage, the descriptors computed from the training set are clustered using K-means (Theodoridis and Koutroumbas, 2006) to generate a colour descriptors dictionary for corrosion. During the classification stage, an image patch is considered to present a colour typical of corrosion if its colour descriptor is similar to at least one of the models in the dictionary, according to the Bhattacharyya distance.

On the contrary, the colour stage of the second method makes use of a colour map of typical corrosion colours. This map is previously computed as a 2-dimensional histogram of hue and saturation values (from the HSV colour space) corresponding to all pixels labelled as corrosion in the training set. Different post-processing methods are proposed to fill the gaps and increase the generalization of the histogram. During the classification stage, the probability that a pixel has a colour similar to corrosion is deemed as proportional to the value of the corresponding bin in the histogram. Both corrosion detection methods provide good classification ratios but the latter is better in terms of computation time. Further evaluation and testing using other colour spaces can be found in Bonnin-Pascual (2017).
Similarly, Medeiros et al. (2010) present a corrosion detector which combines the texture descriptors used by Bento et al. (2009) with colour information using the HSI colour space. The colour descriptors consist in the four first statistical moments extracted from each colour channel histogram. The resulting set of descriptors (texture and colour) is optimized using PCA to eliminate redundant attributes. Finally, the classification is performed using Fisher Linear Discriminant Analysis (FLDA) (Webb and Copsey, 2011) and different subsets of descriptors. The best results are obtained using 13 features combining both texture and colour information, which provide more than 90% of accuracy.

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

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

Tsutsumi et al. (2009) also use a SVM in their approach. It presents a system to categorize images from metallic power transmission towers depending on its deterioration degree. Three classes are defined: early phase, adequate phase and late phase. Two different methods are considered in this approach to represent the colour information which is later used to feed the SVM. The first one consists in using RGB scaling, that is, using a scaled version of the image where the colour of each pixel is computed as the average of the corresponding pixels in the original image. The second approach consists in using the concatenation of the histograms of the three channels in the HSV colour space. Both approaches are assessed using different sizes for the RGB structure or the HSV histogram. The best classification performance provided by the SVM is around 85%, and it is obtained when using an HSV histogram with 192 bins.
Ortiz et al. (2015) present a corrosion detector based on a Shallow Neural Network (SNN) which again combines both colour and texture information. In this approach, the authors compare the results obtained with several combinations of different descriptors. Regarding colour, two descriptors are evaluated: on the one hand, the average value of each channel within a neighbourhood; on the other hand, the stacked 8-bin histograms for downsampled intensity values for each channel in the same neighbourhood. Additionally, both HSV and RGB colour spaces are checked. Regarding texture, center-surround differences are considered in two different ways: signed Surround Differences (SD) between a central pixel and its neighbourhood and 10-bin histograms of uniform Local Binary Patterns (LBP). The number of hidden neurons is also varied, resulting in a total amount of 336 different combinations. The best results are obtained for LBPs with SDs and using 8-bin histograms of hue and saturation channels. A similar approach is presented in Ortiz et al. (2016), where colour is described computing the dominant colours inside a square patch, and texture is described using a number of statistical measures about the SD computed for every colour channel.

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

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

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

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

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

3.3. Discussion

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

Similarly, Table 4 details the main features of the different approaches for corrosion detection reviewed in Section 3.2. Almost all the existing approaches rely on colour and/or texture features, which are usually learned using some machine learning technique. This implies that a dataset is needed for the training stage or to seek for the appropriate configuration that provides a good detection performance.
The idea of using saliency for crack and corrosion detection is exploited by part of these approaches, which allows considering these two (and even other) defective situations together. The latest approaches in these line offer the advantage that they do not require a previous training or parameter-tuning stage, while they are able to perform well in datasets containing images from vessel structures captured under different illumination conditions and from different distances. These techniques are also useful to be executed as a first stage to filter out non-defective situations, prior to executing specific methods for detecting the aforementioned kinds of defects.

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

4. Conclusions

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

Once the agents in charge of collecting inspection data have been reviewed, in the second half of this paper we consider a number of contributions focused on detecting the main defective situations which affect vessel metallic structures, i.e. cracks and corrosion. Regarding cracks, the related literature comprehends a diversity of detection methods, most of which make use of an edge detection technique or involve morphological operators. Another 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.

| Approach                        | Particular technique                  | Reference                                      |
|---------------------------------|---------------------------------------|------------------------------------------------|
| **Edge detection**              |                                       |                                                |
|                                 | Canny                                 | Choi and Kim (2015)                           |
|                                 | LoG                                   | Lim et al. (2014)                             |
|                                 | LoG + labelling + Dijkstra            | Yu et al. (2009)                              |
|                                 | Wavelets                              | Siegel and Gunatilake (1998)*,                |
|                                 |                                       | Subirats et al. (2006),                       |
|                                 |                                       | Chambon et al. (2009)                         |
|                                 | HOG                                   | Eschmann et al. (2012)                        |
|                                 | Image differencing                    | Fujita et al. (2006)                          |
|                                 | Image differencing + Hessian analysis | Fujita and Hamamoto (2011)                    |
|                                 | Image differencing + Hessian analysis + probabilistic relaxation |          |
| **Morphological operators**     |                                       |                                                |
|                                 | 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 Phimpobmongkol (2008)         |
|                                 | Grid method (WDFT)                    | Avril et al. (2004)                           |
|                                 | CNN                                   | Oullette et al. (2003)*,                      |
|                                 |                                       | Zhang et al. (2016)*                          |
|                                 | Clustering                            | Zhao et al. (2015)                            |
| **Other**                       |                                       |                                                |
|                                 | Saliency                              | Bonnin-Pascual and Ortiz (2014a)*,            |
|                                 |                                       | Bonnin-Pascual and Ortiz (2018),              |
|                                 |                                       | Bonnin-Pascual (2017)                         |

* indicates that some machine learning technique is involved.
| Method | Reference | Attributes                                                                 |
|--------|-----------|---------------------------------------------------------------------------|
| SVM    | Bonnin-Pascual and Ortiz (2010) | Contrast, correlation, energy and homogeneity |
| SVM    | Bonnin-Pascual and Ortiz (2014b) | Statistical measures from convolutions |
| SVM    | Ortiz et al. (2015) | Mean colour, stacked histograms |
| SVM    | Ortiz et al. (2016) | Dominant colours, measures from SD |
| CNN    | Idris et al. (2015) | Threshold in saliency |
| CNN    | Roberts (2016) | Threshold in HSY |
| CNN    | Ji et al. (2012) | Threshold in saliency, mean hue, + mean hue |
| CNN    | Tsutsumi et al. (2009) | Mean hue, + mean hue, / LBP |
| CNN    | Yamana et al. (2005) | RGB channels |
| CNN    | Bonnin-Pascual and Ortiz (2014a) | Contrast and symmetry |
| CNN    | Ortiz et al. (2015) | Mean colour, stacked histograms |
| CNN    | Ortiz et al. (2016) | Mean colour, stacked histograms |
| CNN    | Ortiz et al. (2018) | Mean colour, stacked histograms |
| CNN    | Roberts (2016) | Threshold in saliency |
| CNN    | Ji et al. (2012) | Threshold in saliency, mean hue, + mean hue |
| CNN    | Tsutsumi et al. (2009) | Mean hue, + mean hue, / LBP |
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| CNN    | Yamana et al. (2005) | RGB channels |
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| CNN    | Roberts (2016) | Threshold in saliency |
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| CNN    | Tsutsumi et al. (2009) | Mean hue, + mean hue, / LBP |
| CNN    | Yamana et al. (2005) | RGB channels |
concrete surfaces, which typically present a different width and elongation in comparison to the cracks that occur in the metallic structures of vessels. Regarding corrosion, colour and texture are the two main features employed by the existing detection methods. Most of them rely on some machine learning technique to learn how corrosion looks like, which requires an image dataset for training. A special mention must be made to deep learning methods, which are being used in demanding object recognition and classification tasks, including the detection of cracks and corrosion. Generic defect detectors based on saliency must also be kept in mind due to their good detection performance and their usefulness as a previous filter to reduce the false positives of detection algorithms designed for specific defects.

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