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

Francisco Bonnin-Pascual[a,*], Alberto Ortiz[a]

[a] *Department of Mathematics and Computer Science, University of the Balearic Islands, Cra. Valldemossa km 7.5, 07122 Palma de Mallorca, Spain*

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

*Corresponding author: Tel.: +34-971-172-565;
Email address: `xisco.bonnin@uib.es` (Francisco Bonnin-Pascual)

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 m^2 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 give rise to a very significant amount once you factor in the vessel's preparation, use of yard's facilities, cleaning, 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 FP7 and H2020 programmes (projects MINOAS (Eich et al., 2014), INCASS (Ortiz et al., 2017) and ROBINS (Ortiz et al., 2018), among others) and through specific calls, such as Robotics in Application Areas: b) Innovation Actions - Robotics for infrastructure inspection and maintenance, ICT-09-2019-2020 (European Commission, 2017).

Focusing on the particular case of vessel inspection, this paper reviews technological advances which (at least potentially) can facilitate such processes. To be precise, this survey reviews contributions on two key fields. Firstly, Section 2 reviews approaches related to robotic platforms suitable for vessel hull inspection, irrespectively of the mechanical structure of the device and its locomotion approach (e.g. magnetic crawlers, free-floating vehicles, aerial 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 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 literature contains a number of examples about robots devised for inspecting power transmission lines (Katrašnik et al., 2010; Pagnano et al., 2013), dams (Ridao et al., 2010; Cruz et al., 2011), bridges (La et al., 2013; Lim et al., 2014), pipes and sewerage (Mirats and Garthwaite, 2010; Roslin et al., 2012), aircraft skin (Siegel and Gunatilake, 1998; White et al., 2005), etc. In the following sections we focus on those contributions that are of interest for vessel inspection. In Section 2.1, we revise contributions which describe robotic platforms specifically intended for vessel hull inspection, including platforms devised for underwater operation and those developed for being used above the water line, without contemplating aerial platforms. This is because we deal with them separately in Section 2.2, where these are considered together with other aerial platforms intended for the inspection of any kind of infrastructure, since 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 underwater vehicles for the inspection of the submerged part of the vessel hull. As a first example, the vehicle presented 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 even 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 Simultaneous 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 orientation), 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; Eich et al., 2014). 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 attachment. 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 implementation 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 elevated 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 different 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 helicopter (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 or 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 (Bonnin-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	
			Navigation	**Inspection**
Nicinski (1983)	SHIV	ROV ⊗	—	cam/US/mag
Harris and Slate (1999), D'Amaddio et al. (2001)	Lamp Ray	AUV ⊙/≈	LBL	US/mag
Lynn and Bohlander (1999)	—	ROV ≈	—	mag
Trimble and Belcher (2002)	CetusII	AUV ≈	LBL+alt	sonar
Carvalho et al. (2003)	—	ROV ⊗	—	US
Vaganay et al. (2005, 2006), Hover et al. (2007)	HAUV	AUV ≈	DVL+IMU +depth	sonar
Negahdaripour and Firoozfam (2006)	Phantom XTL*	AUV ≈	stereo odo	cam
Kokko (2007)	—	AUV ≈	range	—
Akinfiev et al. (2008)	AURORA	AUV ⊙	opt odo/LBL	US/cam
Menegaldo et al. (2008)	SIRUS	ROV† ⊗	EKF: IMU +wheel odo	US/cam
Walter et al. (2008)	HAUV	AUV ≈	SLAM: sonar	sonar
Li et al. (2009)	SY-2	AUV ≈	DVL+IMU +depth	—
Narewski (2009)	HISMAR	AUV ⊙	opt odo +mag lmk	US
Newsome and Rodocker (2009)	LBC	ROV ⊙/≈	—	cam
Packard et al. (2010)	REMUS	AUV ≈	DVL+IMU +depth	sonar
Eich and Vögele (2011), Fondahl et al. (2012), Ahmed et al. (2015)	MIRA	ROV† ⊗	3D tracker	cam
Schattschneider et al. (2011)	—	—	EKF SLAM: stereo	stereo
Bibuli et al. (2012)	MARC	ROV† ⊗	—	US/cam
Hover et al. (2012)	HAUV	AUV ≈	SLAM: DVL +sonar+cam	sonar/cam
Ishizu et al. (2012)	LBV150*	ROV △/≈	—	cam/stereo
Ferreira et al. (2013)	HROV	AUV △/≈	depth+alt +IMU+DVL	US
Kim and Eustice (2013)	HAUV	AUV ≈	SLAM: cam	sonar/cam
VanMiddlesworth et al. (2013)	HAUV	AUV ≈	SLAM: sonar	sonar
Ozog and Eustice (2015)	HAUV	AUV ≈	SLAM: stereo +DVL	sonar/cam
Ozog et al. (2016)	HAUV	AUV ≈	SLAM: cam	sonar/cam

Name: * indicates a commercial robot used for testing.
Vehicle type: †/non-underwater vehicle, ⊗/magnetic crawler, ⊙/vehicle attached using suction, △/vehicle attached using thrusters and ≈/free-swimming vehicle.
Sensor suite/technique: alt/altimeter, cam/camera, depth/depthmeter, mag/magnetic probe, mag lmk/magnetic landmark, odo/odometry, opt/optical and US/ultrasound probe.

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

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

Type: Heli./helicopter, DF/ducted-fan, 4C/quadcopter, 6C/hexacopter, 8C/octocopter, 8-4C/octoquad Coax./coaxial rotor, Hyb./hybrid and Sim./simulation.
Sensors/tech.: st/stereo rig, cam/camera, opt flow/optical flow and vis odo/visual odometry.
Output: img/image, phys int/physical interaction, thermal/thermal image and recons/reconstruction.

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

* indicates that some machine learning technique is involved.

Table 4: Representative vision-based corrosion detection approaches.

<table>
<tr><th colspan="2">Method</th><th>Reference</th><th>Attributes</th><th>Learning</th><th>Classification</th></tr>
<tr><td rowspan="15">Machine Learning</td><td rowspan="3">Using wavelets</td><td>Siegel and Gunatilake (1998)</td><td>Energy</td><td>Clustering</td><td>Nearest-neighbour</td></tr>
<tr><td>Ghanta et al. (2011)</td><td>Energy and entropy in colour + mean intensity*</td><td colspan="2">LMS</td></tr>
<tr><td>Jahanshahi and Masri (2013)</td><td>Energy in colour</td><td colspan="2">SNN</td></tr>
<tr><td rowspan="4">Using GLCM</td><td>Choi and Kim (2005)</td><td>Metrics from HSI hist, GLCM and morphology*</td><td>Clustering</td><td>Nearest-neighbour</td></tr>
<tr><td>Bento et al. (2009)</td><td>Contrast, correlation, energy and homogeneity</td><td>SOM</td><td>Nearest-neighbour</td></tr>
<tr><td>Bonnin-Pascual (2010)</td><td>RGB stacked hist / HS histogram</td><td>Clustering / Colour map</td><td>Distance threshold / Map query</td></tr>
<tr><td>Medeiros et al. (2010)</td><td>Contrast, correlation, energy and homogeneity and HSI hist moments*</td><td colspan="2">FLDA</td></tr>
<tr><td>Using Law's filters</td><td>Bonnin-Pascual and Ortiz (2014b)</td><td>Statistical measures from convolutions</td><td colspan="2">AdaBoost with CARTs</td></tr>
<tr><td>Using saliency</td><td>Bonnin-Pascual and Ortiz (2014a)</td><td>Contrast and symmetry</td><td colspan="2">PDF estimation</td></tr>
<tr><td rowspan="6">Other</td><td>Yamana et al. (2005)</td><td>RGB channels</td><td colspan="2">SVM</td></tr>
<tr><td>Tsutsumi et al. (2009)</td><td>RGB channels / HSV stacked histograms</td><td colspan="2">SVM</td></tr>
<tr><td>Ortiz et al. (2015)</td><td>Mean colour / stacked histograms + SD / LBP</td><td colspan="2">SNN</td></tr>
<tr><td>Ortiz et al. (2016)</td><td>Dominant colours, measures from SD</td><td colspan="2">SNN</td></tr>
<tr><td>Petricca et al. (2016)</td><td>HSV channels</td><td colspan="2">CNN</td></tr>
<tr><td>Ortiz et al. (2018)</td><td>RGB channels</td><td colspan="2">CNN</td></tr>
<tr><td colspan="2">WS segmentation + mean hue</td><td>Ji et al. (2012)</td><td></td><td></td><td></td></tr>
<tr><td colspan="2">Red channels hist</td><td>Idris et al. (2015)</td><td></td><td></td><td></td></tr>
<tr><td colspan="2">Threshold in HSV</td><td>Roberts (2016)</td><td></td><td></td><td></td></tr>
<tr><td colspan="2">Threshold in saliency</td><td>Bonnin-Pascual and Ortiz (2016, 2018)</td><td></td><td></td><td></td></tr>
</table>

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

Acknowledgements

This work is partially supported by FEDER funding, by the European Social Fund through Ph.D. scholarship FPI10-43175042V (Conselleria d'Educació, Cultura i Universitats, Govern de les Illes Balears), by FP7 project INCASS (GA 605200), by H2020 project ROBINS (GA 779776) and by project nr. AAEE50/2015 (Direcció General d'Innovació i Recerca, Govern de les Illes Balears)

References

Abdel-Qader, I., Abudayyeh, O., Kelly, M. E., 2003. Analysis of Edge-Detection Techniques for Crack Identification in Bridges. Journal of Computing in Civil Engineering 17 (4), 255–263.

Ahmed, M., Eich, M., Bernhard, F., 2015. Design and Control of MIRA: a Lightweight Climbing Robot for Ship Inspection. International Letters of Chemistry, Physics and Astronomy 55, 128–135.

Akinfiev, T. S., Armada, M. A., Fernandez, R., 2008. Nondestructive Testing of the State of a Ship's Hull with an Underwater Robot. Russian Journal of Nondestructive Testing 44 (9), 626–633.

Alexis, K., Darivianakis, G., Burri, M., Siegwart, R., 2016. Aerial Robotic Contact-based Inspection: Planning and Control. Autonomous Robots 40 (4), 631–655.

Amano, T., 2006. Correlation Based Image Defect Detection. In: International Conference on Pattern Recognition. pp. 163–166.

Avril, S., Vautrin, A., Surrel, Y., 2004. Grid Method: Application to the Characterization of Cracks. Experimental Mechanics 44 (1), 37–43.

Belcher, E., Hanot, W., Burch, J., 2002. Dual-Frequency Identification Sonar (DIDSON). In: International Symposium on Underwater Technology. pp. 187–192.

Bento, M. P., de Medeiros, F. N. S., de Paula Jr., I. C., Ramalho, G. L. B., 2009. Image Processing Techniques Applied for Corrosion Damage Analysis. In: Brazilian Symposium on Computer Graphics and Image Processing.

Bibuli, M., Bruzzone, G., Bruzzone, G., Caccia, M., Giacopelli, M., Petitti, A., Spirandelli, E., 2012. MARC: Magnetic Autonomous Robotic Crawler Development and Exploitation in the MINOAS Project. In: International Conference on Computer Applications and Information Technology in the Maritime Industries. pp. 62–75.

Bonnin-Pascual, F., 2010. Detection of Cracks and Corrosion for Automated Vessels Visual Inspection. Master's thesis, University of the Balearic Islands.
URL http://xiscobonnin.github.io/mthesis.pdf

Bonnin-Pascual, F., 2017. Contributions to Robot-based Vessel Visual Inspection. Ph.D. thesis, University of the Balearic Islands. URL http://xiscobonnin.github.io/dthesis.pdf

Bonnin-Pascual, F., Garcia-Fidalgo, E., Ortiz, A., 2012. Semi-autonomous Visual Inspection of Vessels Assisted by an Unmanned Micro Aerial Vehicle. In: IEEE/RSJ International Conference on Intelligent Robots and Systems. pp. 3955–3961.

Bonnin-Pascual, F., Ortiz, A., 2014a. A Probabilistic Approach for Defect Detection based on Saliency Mechanisms. In: IEEE International Conference on Emerging Technologies and Factory Automation.

Bonnin-Pascual, F., Ortiz, A., 2014b. Corrosion Detection for Automated Visual Inspection. In: Aliofkhazraei, D. M. (Ed.), Developments in Corrosion Protection. InTech, Ch. 25, pp. 619–632.

Bonnin-Pascual, F., Ortiz, A., 2016. A Flying Tool for Sensing Vessel Structure Defects using Image Contrast-based Saliency. IEEE Sensors Journal 16 (15), 6114–6121.

Bonnin-Pascual, F., Ortiz, A., 2017. A Saliency-boosted Corrosion Detector for the Visual Inspection of Vessels. In: Artificial Intelligence Research and Development. IOS Press, (in press).

Bonnin-Pascual, F., Ortiz, A., 2018. A Novel Approach for Defect Detection on Vessel Structures using Saliency-related Features. Ocean Engineering 149, 397–408.

Bonnin-Pascual, F., Ortiz, A., Garcia-Fidalgo, E., Company, J. P., 2015. A Micro-Aerial Platform for Vessel Visual Inspection based on Supervised Autonomy. In: IEEE/RSJ International Conference on Intelligent Robots and Systems. pp. 46–52.

Bonnin-Pascual, F., Ortiz, A., Garcia-Fidalgo, E., Company, J. P., 2017. Testing the Control Architecture of a Micro-Aerial Vehicle for Visual Inspection of Vessels. In: Robot 2017: Third Iberian Robotics Conference. Advances in Robotics. Vol. 693. Springer International Publishing, pp. 693–705.

Bonnin-Pascual, F., Ortiz, A., Garcia-Fidalgo, E., Company, J. P., 2019. A Reconfigurable Framework to Turn a MAV into an Effective Tool for Vessel Inspection. Robotics and Computer-integrated Manufacturing 56, 191–211.

Burri, M., Nikolic, J., Hürzeler, C., Caprari, G., Siegwart, R., 2012. Aerial Service Robots for Visual Inspection of Thermal Power Plant Boiler Systems. In: International Conference on Applied Robotics for the Power Industry. pp. 70–75.

Cacace, J., Finzi, A., Lippiello, V., Loianno, G., Sanzone, D., 2015. Aerial Service Vehicles for Industrial Inspection: Task Decomposition and Plan Execution. Applied Intelligence 42 (1), 49–62.

Campo, L. V., Corrales, J. C., Ledezma, A., 2016. An Aerial Autonomous Robot for Complete Coverage Outdoors. In: Workshop of Physical Agents.

Campoy, P., Garcia, P. J., Barrientos, A., del Cerro, J., Aguirre, I., Roa, A., Garcia, R., Muñoz, J. M., 2001. An Stereoscopic Vision System Guiding an Autonomous Helicopter for Overhead Power Cable Inspection. In: International Workshop RobVis.

Canny, J., 1986. A Computational Approach To Edge Detection. IEEE Transactions on Pattern Analysis and Machine Intelligence 8 (6), 679–698.

Carvalho, A. A., Sagrilo, L. V. S., Silva, I. C., Rebello, J. M. A., Carneval, R. O., 2003. On the Reliability of an Automated Ultrasonic System for Hull Inspection in Ship-based Oil Production Units. Applied Ocean Research 25, 235–241.

Chambon, S., Subirats, P., Dumoulin, J., 2009. Introduction of a Wavelet Transform based on 2D Matched Filter in a Markov Random Field for Fine Structure Extraction: Application on Road Crack Detection. In: IS&T/SPIE Electronic Imaging - Image Processing: Machine Vision Applications II.

Chin, R. T., Harlow, C. A., 1982. Automated Visual Inspection: A Survey. IEEE Transactions on Pattern Analysis and Machine Intelligence 4 (6), 557–573.

Cho, S. H., Hisatomi, K., Hashimoto, S., 1998. Cracks and Displacement Feature Extraction of the Concrete Block Surface. In: IAPR Workshop on Machine Vision Applications. pp. 246–249.

Choi, K. Y., Kim, S. S., 2005. Morphological Analysis and Classification of Types of Surface Corrosion Damage by Digital Image Processing. Corrosion Science 47 (1), 1–15.

Choi, S.-s., Kim, E.-k., 2015. Building Crack Inspection using Small UAV. In: International Conference on Advanced Communication Technology. pp. 235–238.

Cruz, N. A., Matos, A. C., Almeida, R. M., Ferreira, B. M., Abreu, N., 2011. TriMARES - a Hybrid AUV/ROV for Dam Inspection. In: IEEE/MTS OCEANS Conference. pp. 1–7.

D'Amaddio, E., Harris, S., Bergeron, E. amd Slate, E., 2001. Method and apparatus for inspecting a submerged structure.

Durrant-Whyte, H., Bailey, T., 2006. Simultaneous Localisation and Mapping (SLAM): Part I The Essential Algorithms. IEEE Robotics and Automation Magazine 2, 99–110.

Eich, M., Bonnin-Pascual, F., Garcia-Fidalgo, E., Ortiz, A., Bruzzone, G., Koveos, Y., Kirchner, F., 2014. A Robot Application to Marine Vessel Inspection. Journal of Field Robotics 31 (2), 319–341.

Eich, M., Vögele, T., 2011. Design and Control of a Lightweight Magnetic Climbing Robot for Vessel Inspection. In: IEEE Mediterranean Conference on Control and Automation. pp. 1200–1205.

Ellenberg, A., Kontsos, A., Moon, F., Bartoli, I., 2016. Bridge Related Damage Quantification using Unmanned Aerial Vehicle Imagery. Structural Control and Health Monitoring 23, 1168–1179.

Eschmann, C., Kuo, C. M., Kuo, C. H., Boller, C., 2012. Unmanned Aircraft Systems for Remote Building Inspection and Monitoring. In: European Workshop on Structural Health Monitoring. pp. 1–8.

European Commission, 2017. Robotics in Application Areas. `http://ec.europa.eu/research/participants/portal/desktop/en/opportunities/h2020/topics/ict-09-2019-2020.html`, (accessed July 19, 2019).

Fang, Z., Yang, S., Jain, S., Dubey, G., Roth, S., Maeta, S., Nuske, S., Zhang, Y., Scherer, S., 2017. Robust Autonomous Flight in Constrained and Visually Degraded Shipboard Environments. Journal of Field Robotics 34 (1), 25–52.

Fawcett, T., 2006. An Introduction to ROC Analysis. Pattern Recognition Letters 27 (8), 861–874.

Ferreira, C. Z., Conte, G. Y. C., Avila, J. P. J., Pereira, R. C., Ribeiro, T. M. C., 2013. Underwater Robotic Vehicle for Ship Hull Inspection: Control System Architecture. In: International Congress of Mechanical Engineering.

Fondahl, K., Eich, M., Wollenberg, J., Kirchner, F., 2012. A Magnetic Climbing Robot for Marine Inspection Services. In: International Conference on Computer Applications and Information Technology in the Maritime Industries. pp. 92–102.

Fox, D., Burgard, W., Thrun, S., 1997. The Dynamic Window Approach to Collision Avoidance. IEEE Robotics and Automation Magazine 4 (1), 23–33.

Freund, Y., Schapire, R. E., 1999. A Short Introduction to Boosting. Journal of Japanese Society for Artificial Intelligence 14 (5), 771–780.

Fujita, Y., Hamamoto, Y., 2011. A Robust Automatic Crack Detection Method for Noisy Concrete Surfaces. Machine Vision and Applications 22 (2), 245–254.

Fujita, Y., Mitani, Y., Hamamoto, Y., 2006. A Method for Crack Detection on a Concrete Structure. In: International Conference on Pattern Recognition.

Ghanta, S., Karp, T., Lee, S., 2011. Wavelet Domain Detection of Rust in Steel Bridge Images. In: IEEE International Conference on Acoustics, Speech and Signal Processing. pp. 1033–1036.

Gohl, P., Burri, M., Omari, S., Rehder, J., Nikolic, J., Achtelik, M., Siegwart, R., 2014. Towards Autonomous Mine Inspection. In: International Conference on Applied Robotics for the Power Industry.

Hallermann, N., Morgenthal, G., 2014. Visual Inspection Strategies for Large Bridges using Unmanned Aerial Vehicles (UAV). In: International Conference on Bridge Maintenance, Safety and Management.

Haralick, R. M., Shanmugam, K., Dinstein, I., 1973. Textural Features for Image Classification. IEEE Transactions on Systems, Man and Cybernetics 3 (6), 610–621.

Harris, S. E., Slate, E. V., 1999. Lamp Ray: Ship Hull Assessment for Value, Safety and Readiness. In: IEEE/MTS OCEANS Conference. pp. 493–500.

Høglund, S., 2014. Autonomous Inspection of Wind Turbines and Buildings using an UAV. Master's thesis, Norwegian University of Science and Technology.
URL http://hdl.handle.net/11250/261287

Hover, F., Vaganay, J., Elkins, M., Willcox, S., Polidoro, V., Morash, J., Damus, R., Desset, S., 2007. A Vehicle System for Autonomous Relative Survey of In-Water Ships. Marine Technology Society Journal 41 (2), 44–55.

Hover, F. S., Eustice, R. M., Kim, A., Englot, B., Johannsson, H., Kaess, M., Leonard, J. J., 2012. Advanced Perception, Navigation and Planning for Autonomous In-Water Ship Hull Inspection. International Journal of Robotics Research 31 (12), 1445–1464.

Huang, G. B., Zhou, H., Ding, X., Zhang, R., 2012. Extreme Learning Machine for Regression and Multiclass Classification. IEEE Transactions on Systems, Man and Cybernetics - Part B: Cybernetics 42 (2), 513–529.

Huerzeler, C., Caprari, G., Zwicker, E., Marconi, L., 2012. Applying Aerial Robotics for Inspections of Power and Petrochemical Facilities. In: International Conference on Applied Robotics for the Power Industry. pp. 167–172.

Idris, S. A., Jafar, F. A., Saffar, S., 2015. Improving Visual Corrosion Inspection Accuracy with Image Enhancement Filters. In: International Conference on Ubiquitous Robots and Ambient Intelligence. pp. 129–132.

Ishizu, K., Sakagami, N., Ishimaru, K., Shibata, M., Onishi, H., Murakami, S., Kawamura, S., 2012. Ship Hull Inspection using A Small Underwater Robot With A Mechanical Contact Mechanism. In: IEEE/MTS OCEANS Conference. pp. 1–6.

Jahanshahi, M. R., Kelly, J. S., Masri, S. F., Sukhatme, G. S., 2009. A Survey and Evaluation of Promising Approaches for Automatic Image-based Defect Detection of Bridge Structures. Structure and Infrastructure Engineering 5 (6), 455–486.

Jahanshahi, M. R., Masri, S. F., 2013. Effect of Color Space, Color Channels, and Sub-Image Block Size on the Performance of Wavelet-based Texture Analysis Algorithms: An Application to Corrosion Detection on Steel Structures. In: Computing in Civil Engineering. pp. 685–692.

Jahanshahi, M. R., Masri, S. F., Padgett, C. W., Sukhatme, G. S., 2013. An Innovative Methodology for Detection and Quantification of Cracks Through Incorporation of Depth Perception. Machine Vision and Applications 24 (2), 227–241.

Ji, G., Zhu, Y., Zhang, Y., 2012. The Corroded Defect Rating System of Coating Material Based on Computer Vision. In: Transactions on Edutainment VIII. Vol. LNCS 7220. pp. 210–220.

Jia, H., Murphey, Y. L., Shi, J., Chang, T.-S., 2004. An Intelligent Real-time Vision System for Surface Defect Detection. In: International Conference on Pattern Recognition. Vol. III. pp. 239–242.

Jimenez-Cano, A. E., Braga, J., Heredia, G., Ollero, A., 2015. Aerial Manipulator for Structure Inspection by Contact from the Underside. In: IEEE/RSJ International Conference on Intelligent Robots and Systems. pp. 1879–1884.

Johannsson, H., Kaess, M., Englot, B., Hover, F., Leonard, J., 2010. Imaging Sonar-aided Navigation for Autonomous Underwater Harbor Surveillance. In: IEEE/RSJ International Conference on Intelligent Robots and Systems. pp. 4396–4403.

Jolliffe, I., 2002. Principal Component Analysis. Springer.

Jones, D., 2005. Power Line Inspection - An UAV Concept. In: The IEE Forum on Autonomous Systems.

Kaess, M., Ranganathan, A., Dellaert, F., 2008. iSAM: Incremental Smoothing and Mapping. IEEE Transactions on Robotics 24 (6), 1365–1378.

Kaiser, H. F., 1958. The Varimax Criterion for Analytic Rotation in Factor Analysis. Psychometrika 23 (3), 187–200.

Katrašnik, J., Pernuš, F., Likar, B., 2010. A Survey of Mobile Robots for Distribution Power Line Inspection. IEEE Transactions on Power Delivery 25 (1), 485–493.

Kim, A., Eustice, R., 2009. Pose-graph Visual SLAM with Geometric Model Selection for Autonomous Underwater Ship Hull Inspection. In: IEEE/RSJ International Conference on Intelligent Robots and Systems. pp. 1559–1565.

Kim, A., Eustice, R. M., 2013. Real-Time Visual SLAM for Autonomous Underwater Hull Inspection using Visual Saliency. IEEE Transactions on Robotics 29 (3), 719–733.

Kohonen, T., 2001. Self-Organizing Maps. Springer.

Kokko, M. A., 2007. Range-based Navigation of AUVs Operating Near Ship Hulls. Master's thesis, Massachusetts Institute of Technology. URL https://dspace.mit.edu/handle/1721.1/40292

Krizhevsky, A., Sutskever, I., Hinton, G. E., 2012. ImageNet Classification with Deep Convolutional Neural Networks. In: Neural Information Processing Systems.

La, H. M., Lim, R. S., Basily, B., Gucunski, N., Yi, J., Maher, A., Romero, F. A., Parvardeh, H., 2013. Autonomous Robotic System for High-Efficiency Non-Destructive Bridge Deck Inspection and Evaluation. In: IEEE International Conference on Automation Science and Engineering. pp. 1053–1058.

Law, K. I., 1980. Textured Image Segmentation. Tech. Rep. 940, Image Processing Institute, University of Southern California.

Li, Y., Pang, Y., Chen, Y., Wan, L., Zou, J., 2009. A Hull-Inspect ROV Control System Architecture. China Ocean Engineering 23 (4), 751–761.

Lim, R. S., La, H. M., Sheng, W., 2014. A Robotic Crack Inspection and Mapping System for Bridge Deck Maintenance. IEEE Transactions on Automation Science and Engineering 11 (2), 367–378.

Lippiello, V., Siciliano, B., 2012. Wall Inspection Control of a VTOL Unmanned Aerial Vehicle based on a Stereo Optical Flow. In: IEEE/RSJ International Conference on Intelligent Robots and Systems. pp. 4296–4302.

Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.-Y., Berg, A. C., 2016. SSD: Single Shot MultiBox Detector. In: European Conference on Computer Vision. pp. 21–37.

Lynn, D. C., Bohlander, G. S., 1999. Performing Ship Hull Inspections using a Remotely Operated Vehicle. In: IEEE/MTS OCEANS Conference. Vol. 2. pp. 555–562.

Malamas, E. N., Petrakis, E. G. M., Zervakis, M., Petit, L., Legat, J.-D., 2003. A Survey on Industrial Vision Systems, Applications and Tools. Image and Vision Computing 21, 171–188.

Marconi, L., Basile, F., Caprari, G., Carloni, R., Chiacchio, P., Hurzeler, C., Lippiello, V., Naldi, R., Nikolic, J., Siciliano, B., Stramigioli, S., Zwicker, E., 2012. Aerial Service Robotics: the AIRobots Perspective. In: International Conference on Applied Robotics for the Power Industry. pp. 64–69.

Martinez, C., Sampedro, C., Chauhan, A., Campoy, P., 2014. Towards Autonomous Detection and Tracking of Electric Towers for Aerial Power Line Inspection. In: International Conference on Unmanned Aircraft Systems. pp. 284–295.

Máthé, K., Buşoniu, L., 2015. Vision and Control for UAVs: A Survey of General Methods and of Inexpensive Platforms for Infrastructure Inspection. Sensors 15, 14887–14916.

McAree, O., Aitken, J. M., Veres, S. M., 2016. A Model based Design Framework for Safety Verification of a Semi-Autonomous Inspection Drone. In: UK Automatic Control Conference.

Medeiros, F. N. S., Ramalho, G. L. B., Bento, M. P., Medeiros, L. C. L., 2010. On the Evaluation of Texture and Color Features for Nondestructive Corrosion Detection. EURASIP Journal on Advances in Signal Processing.

Menegaldo, L. L., Santos, M., Ferreira, G. A. N., Siqueira, R. G., Moscato, L., 2008. SIRUS: A Mobile Robot for Floating Production Storage and Offloading (FPSO) Ship Hull Inspection. In: IEEE International Workshop on Advanced Motion Control. pp. 27–32.

Meng, L., Wang, Z., Fujikawa, Y., Oyanagi, S., 2015. Detecting Cracks on a Concrete Surface using Histogram of Oriented Gradients. In: International Conference on Advanced Mechatronic Systems. pp. 103–107.

Michael, N., Shen, S., Motha, K., Mulgaonkar, Y., Kumar, V., Nagatani, K., Okada, Y., Kiribayashi, S., Otake, K., Yoshida, K., Ohno, K., Takeuchi, E., Tadokoro, S., 2012. Collaborative Mapping of an Earthquake-Damaged Building via Ground and Aerial Robots. Journal of Field Robotics 29 (5), 832–841.

Mirats, J. M., Garthwaite, W., 2010. Robotic Devices for Water Main In-Pipe Inspection: A Survey. Journal of Field Robotics 27 (4), 491–508.

Morgenthal, G., Hallermann, N., 2014. Quality Assessment of Unmanned Aerial Vehicle (UAV) Based Visual Inspection of Structures. Advances in Structural Engineering 17 (3), 289–302.

Mumtaz, M., Masoor, A. B., Masood, H., 2010. A New Approach to Aircraft Surface Inspection based on Directional Energies of Texture. In: International Conference on Pattern Recognition. pp. 4404–4407.

Narewski, M., 2009. Hismar - Underwater Hull Inspection and Cleaning System As a Tool for Ship Propulsion System Performance Increase. Journal of Polish CIMAC 4 (2), 227–234.

Negahdaripour, S., Firoozfam, P., 2006. An ROV Stereovision System for Ship-Hull Inspection. IEEE Journal of Oceanic Engineering 31 (3), 551–564.

Newman, T. S., 1995. A Survey of Automated Visual Inspection. Computer Vision and Image Understanding 61 (2), 321–262.

Newsome, S. M., Rodocker, J., 2009. Effective Technology for Underwater Hull and Infrastructure Inspection. In: IEEE/MTS OCEANS Conference. pp. 1–6.

Nicinski, S. A., 1983. Development of a Remotely Operated Ship Hull Inspection Vehicle. In: IEEE/MTS OCEANS Conference. pp. 583–587.

Nieniewski, M., Chmielewski, L., Jóźwik, A., Skłodowski, M., 1999. Morphological Detection and Feature-based Classification of Cracked Regions in Ferrites. Machine Graphics and Vision 8 (4), 699–712.

Nikolic, J., Burri, M., Rehder, J., Leutenegger, S., Huerzeler, C., Siegwart, R., 2013. A UAV System for Inspection of Industrial Facilities. In: IEEE Aerospace Conference. pp. 1–8.

Nikolic, J., Rehder, J., Burri, M., Gohl, P., Leutenegger, S., Furgale, P. T., Siegwart, R., 2014. A Synchronized Visual-Inertial Sensor System with FPGA Pre-Processing for Accurate Real-Time SLAM. In: IEEE International Conference on Robotics and Automation.

Omari, S., Gohl, P., Burri, M., Achtelik, M., Siegwart, R., 2014. Visual Industrial Inspection using Aerial Robots. In: International Conference on Applied Robotics for the Power Industry. pp. 1–5.

Ortiz, A., Bonnin-Pascual, F., Garcia-Fidalgo, E., 2014. Vessel Inspection: A Micro-Aerial Vehicle-based Approach. Journal of Intelligent and Robotic Systems 76, 151–167.

Ortiz, A., Bonnin-Pascual, F., Garcia-Fidalgo, E., Company-Corcoles, J. P., 2015. Visual Inspection of Vessels by means of a Micro-Aerial Vehicle: an Artificial Neural Network Approach for Corrosion Detection. In: Reis, L. P., Moreira, A. P., Lima, P. U., Montano, L., Muñoz-Martinez, V. (Eds.), Robot 2015: Second Iberian Robotics Conference. Advances in Robotics. Vol. 418. Springer International Publishing, pp. 223–234.

Ortiz, A., Bonnin-Pascual, F., Garcia-Fidalgo, E., Company-Corcoles, J. P., 2016. Vision-Based Corrosion Detection Assisted by a Micro-Aerial Vehicle in a Vessel Inspection Application. Sensors 16 (2118).

Ortiz, A., Bonnin-Pascual, F., Garcia-Fidalgo, E., Company-Corcoles, J. P., 2017. The INCASS Project Approach towards Automated Visual Inspection of Vessels. In: Jornadas Nacionales de Robótica (Spanish Robotics Workshop).

Ortiz, A., Bonnin-Pascual, F., Gibbins, A., Apostolopoulou, P., Bateman, W., Eich, M., Spadoni, F., Caccia, M., Drikos, L., 2010. First Steps Towards a Roboticized Visual Inspection System for Vessels. In: IEEE International Conference on Emerging Technologies and Factory Automation. pp. 1–6.

Ortiz, A., Yao, K., Bonnin-Pascual, F., Garcia-Fidalgo, E., Company-Corcoles, J. P., 2018. New Steps towards the Integration of Robotic and Autonomous Systems in the Inspection of Vessel Holds. In: Jornadas Nacionales de Robótica (Spanish Robotics Workshop).

Oullette, R., Browne, M., Hirasawa, K., 2004. Genetic Algorithm Optimization of a Convolutional Neural Network for Autonomous Crack Detection. In: Congress on Evolutionary Computation. pp. 516–521.

Ozog, P., Carlevaris-Bianco, N., Kim, A., Eustice, R. M., 2016. Long-term Mapping Techniques for Ship Hull Inspection and Surveillance using an Autonomous Underwater Vehicle. Journal of Field Robotics 33 (3), 265–289.

Ozog, P., Eustice, R. M., 2015. Identifying Structural Anomalies in Image Reconstructions of Underwater Ship Hulls. In: IEEE/MTS OCEANS Conference.

Packard, G. E., Stokey, R., Christenson, R., Jaffre, F., Purcell, M., Littlefield, R., 2010. Hull Inspection and Confined Area Search Capabilities of REMUS Autonomous Underwater Vehicle. In: IEEE/MTS OCEANS Conference.

Pagnano, A., Höpf, M., Teti, R., 2013. A Roadmap for Automated Power Line Inspection. Maintenance and Repair. In: CIRP Conference on Intelligent Computation in Manufacturing Engineering. pp. 234–239.

Peres Castilho, H., Caldas Pinto, J. R., Limas Serafim, A., 2006. NN Automated Defect Detection Based on Optimized Thresholding. In: International Conference on Image Analysis and Recognition. pp. 790–801.

Petricca, L., Moss, T., Figueroa, G., Broen, S., 2016. Corrosion Detection using A.I.: A Comparison of Standard Computer Vision Techniques and Deep Learning Model. In: International Conference on Computer Science, Engineering and Information Technology. pp. 91–99.

Qu, Z., Lin, L.-D., Guo, Y., Wang, N., 2015. An Improved Algorithm for Image Crack Detection based on Percolation Model. IEEJ Transactions on Electrical and Electronic Engineering 10 (2), 214–221.

Quater, P. B., Grimaccia, F., Leva, S., Mussetta, M., Aghaei, M., 2014. Light Unmanned Aerial Vehicles (UAVs) for Cooperative Inspection of PV Plants. IEEE Journal of Photovoltaics 4 (4), 1107–1113.

Reed, S., Cormack, A., Hamilton, K., Tena Ruiz, I., Lane, D., 2006. Automatic Ship Hull Inspection using Unmanned Underwater Vehicles (UUV's). In: International Symposium on Technology and the Mine Problem.

Ren, S., He, K., Girshick, R., Sun, J., 2015. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. In: Advances in Neural Information Processing Systems. pp. 91–99.

Ridao, P., Carreras, M., Ribas, D., Garcia, R., 2010. Visual Inspection of Hydroelectric Dams using an Autonomous Underwater Vehicle. Journal of Field Robotics 27 (6), 759–778.

Roberts, N. S., 2016. Corrosion Detection in Enclosed Environments using Remote Systems. Master's thesis, Alfred University.
URL `http://hdl.handle.net/10829/7248`

Roslin, N. S., Anuar, A., Jalal, M. F. A., Sahari, K. S. M., 2012. A Review: Hybrid Locomotion of In-pipe Inspection Robot. In: International Symposium on Robotics and Intelligent Sensors. Vol. 41. pp. 1456–1462.

Sa, I., Hrabar, S., Corke, P., 2015. Inspection of Pole-Like Structures using a Visual-Inertial Aided VTOL Platform with Shared Autonomy. Sensors 15 (9), 22003–22048.

Sampedro, C., Martinez, C., Chauhan, A., Campoy, P., 2014. A Supervised Approach to Electric Tower Detection and Classification for Power Line Inspection. In: IEEE World Congress on Computational Intelligence.

Santamaria, A., Andrade, J., 2014. Hierarchical Task Control for Aerial Inspection. In: euRathlon-ARCAS Workshop and Summer School on Field Robotics.

Satler, M., Unetti, M., Giordani, N., Avizzano, C. A., Tripicchio, P., 2014. Towards an Autonomous Flying Robot for Inspections in Open and Constrained Spaces. In: Multi-Conference on Systems, Signals and Devices.

Schattschneider, R., Maurino, G., Wang, W., 2011. Towards Stereo Vision SLAM based Pose Estimation for Ship Hull Inspection. In: IEEE/MTS OCEANS Conference.

Serrano, N. E., 2011. Autonomous Quadrotor Unmanned Aerial Vehicle for Culvert Inspection. Master's thesis, Massachusetts Institute of Technology.

URL http://hdl.handle.net/1721.1/67752

Siegel, M., Gunatilake, P., 1998. Remote Enhanced Visual Inspection of Aircraft by a Mobile Robot. In: IEEE Workshop on Emerging Technologies, Intelligent Measurement and Virtual Systems for Instrumentation and Measurement.

Simonyan, K., Zisserman, A., 2014. Very Deep Convolutional Networks for Large-Scale Image Recognition. CoRR abs/1409.1556.

Snavely, K. N., 2008. Scene reconstruction and visualization from internet photo collections. Ph.D. thesis, University of Washington.

Sorncharean, S., Phiphobmongkol, S., 2008. Crack Detection on Asphalt Surface Image using Enhanced Grid Cell Analysis. In: IEEE International Symposium on Electronic Design, Test and Applications.

Subirats, P., Dumoulin, J., Legeay, V., Barba, D., 2006. Automation of Pavement Surface Crack Detection using the Continuous Wavelet Transform. In: IEEE International Conference on Image Processing. pp. 3037–3040.

Tanaka, N., Uematsu, K., 1998. A Crack Detection Method in Road Surface Images Using Morphology. In: IAPR Workshop on Machine Vision Applications. pp. 154–157.

Theodoridis, S., Koutroumbas, K., 2006. Pattern Recognition, 3rd Edition. Academic Press.

Trimble, G. M., Belcher, E. O., 2002. Ship Berthing and Hull Inspection using the CetusII AUV and MIRIS High-Resolution Sonar. In: IEEE/MTS OCEANS Conference.

Tsutsumi, F., Murata, H., Onoda, T., Oguri, O., Tanaka, H., 2009. Automatic Corrosion Estimation using Galvanized Steel Images on Power Transmission Towers. In: Transmission and Distribution Conference and Exposition: Asia and Pacific.

United Nations Conference on Trade and Development, 2015. Review of Maritime Transport. United Nations Publication, UNCTAD/RMT/2015.

Vaganay, J., Elkins, M., Esposito, D., O'Halloran, W., Hover, F., Kokko, M., 2006. Ship Hull Inspection with the HAUV: US Navy and NATO Demonstrations Results. In: IEEE/MTS OCEANS Conference.

Vaganay, J., Elkins, M. L., Willcox, S., Hover, F. S., Damus, R. S., Desset, S., Morash, J. P., Polidoro, V. C., 2005. Ship Hull Inspection by Hull-Relative Navigation and Control. In: IEEE/MTS OCEANS Conference.

VanMiddlesworth, M., Kaess, M., Hover, F., Leonard, J. J., 2013. Mapping 3D Underwater Environments with Smoothed Submaps. In: International Conference on Field and Service Robotics. pp. 17–30.

Vincent, L., Soille, P., 1991. Watersheds in Digital Spaces: An Efficient Algorithm Based on Immersion Simulations. IEEE Transactions on Pattern Analysis and Machine Intelligence 13 (6), 583–598.

Walter, M., Hover, F., Leonard, J., 2008. SLAM for Ship Hull Inspection using Exactly Sparse Extended Information Filters. In: IEEE International Conference on Robotics and Automation. pp. 1463–1470.

Webb, A. R., Copsey, K. D., 2011. Statistical Pattern Recognition, 3rd Edition. Wiley.

White, T. S., Alexander, R., Callow, G., Cooke, A., Harris, S., Sargent, J., 2005. A Mobile Climbing Robot for High Precision Manufacture and Inspection of Aerostructures. International Journal of Robotics Research 24 (7), 589–598.

Wu, H., Lv, M., Liu, C. A., Liu, C. Y., 2012. Planning Efficient and Robust Behaviors for Model-based Power Tower Inspection. In: International Conference on Applied Robotics for the Power Industry. pp. 163–166.

Xie, X., 2008. A Review of Recent Advances in Surface Defect Detection using Texture Analysis Techniques. Electronic Letters on Computer Vision and Image Analysis 7 (3), 1–22.

Yamaguchi, T., Hashimoto, S., 2006. Image Processing based on Percolation Model. IEICE Transactions on Information and Systems 89 (7), 2044–2052.

Yamaguchi, T., Hashimoto, S., 2010. Fast Crack Detection Method for Large-size Concrete Surface Images using Percolation-based Image Processing. Machine Vision and Applications 21 (5), 797–809.

Yamana, M., Murata, H., Onoda, T., Ohashi, T., Kato, S., 2005. Development of System for Crossarm Reuse Judgment on the Basis of Classification of Rust Images using Support Vector Machine. In: IEEE International Conference on Tools with Artificial Intelligence.

Yoshioka, M., Omatu, S., 2009. Defect Detection Method using Rotational Morphology. Artificial Life and Robotics 14 (1), 20–23.

Yu, S.-N., Jang, J.-H., Han, C.-S., 2007. Auto Inspection System using a Mobile Robot for Detecting Concrete Cracks in a Tunnel. Automation in Construction 16 (3), 255–261.

Zainal Abidin, Z., Arshad, M. R., 2006. Visual Servoing with Application to ROV for Ship Hull Inspection. In: International Conference on Man-Machine Systems.

Zhang, L., Yang, F., Zhang, Y. D., Zhu, Y. J., 2016. Road Crack Detection using Deep Convolutional Neural Network. In: IEEE International Conference on Image Processing. pp. 3708–3712.

Zhang, W., Zhang, Z., Qi, D., Liu, Y., 2014. Automatic Crack Detection and Classification Method for Subway Tunnel Safety Monitoring. Sensors 14, 19307–19328.

Zhao, G., Wang, T., Ye, J., 2015. Anisotropic Clustering on Surfaces for Crack Extraction. Machine Vision and Applications 26 (5), 675–688.

Zheng, H., Kong, L. X., Nahavandi, S., 2002. Automatic Inspection of Metallic Surface Defects using Genetic Algorithms. Journal of Materials Processing Technology 125-126, 427–433.