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A novel approach for defect detection on vessel structures using saliency-related features

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ABSTRACT

Seagoing vessels have to undergo regular visual inspections in order to detect defects such as cracks and corrosion before they result into catastrophic consequences. These inspections are currently performed manually by ship surveyors at a great cost, so that any level of assistance during the inspection process by means of e.g. a fleet of robots capable of defect detection would significatively decrease the inspection cost. In this paper, we describe a novel framework for visually detecting the aforementioned defects. This framework is generic and flexible in the sense that it can be easily configured to compute the features that perform better for the inspection at hand. Making use of this framework and inspired by the idea of conspicuity, this work considers contrast and symmetry as features for detecting defects and shows their usefulness for the case of vessels. Three different combination operators are additionally tested in order to merge the information provided by these features and improve the detection performance. Experimental results for different configurations of the detection framework show better classification rates than state of the art methods and prove its usability for images collected by a micro-aerial robotic platform intended for visual inspection.

1. Introduction

Vessels are nowadays one of the most cost effective ways to transport goods around the world. Despite the efforts to avoid maritime accidents and wreckages, these still occur, and, from time to time, have catastrophic consequences in environmental, human and/or economic terms. Structural failures are the main cause of these accidents and, as such, Classification Societies impose extensive inspection schemes in order to ensure the structural integrity of vessels.

An important part of the vessel maintenance has to do with the visual inspection of the internal and external parts of the vessel hull. They can be affected by different kinds of defects typical of steel surfaces and structures, such as cracks and corrosion. These defects are indicators of the state of the metallic surface and, as such, an early detection prevents the structure from buckling and/or fracturing.

To carry out this task, the vessel has to be emptied and situated in a dockyard where scaffoldings are installed to allow the human inspectors to access the highest parts of the vessel structure (higher than 30 m in some cases). Taking into account the huge dimensions of some vessels, this process can mean the visual assessment of more than 600,000 m^2 of steel. Besides, the surveys are on many occasions performed in hazardous environments for which the access is usually difficult and the operational conditions turn out to be sometimes extreme for human operation. Moreover, total expenses involved by the infrastructure needed for close-up inspection of the hull can reach up to one million dollars for certain sorts of vessels (e.g. Ultra Large Crude Carriers). Therefore, it is clear that any level of automation of the inspection process that can lead to a reduction of the inspection time, a reduction of the financial costs, and/or an increase in the safety of the operation, is fully justified.

The EU-funded projects MINOAS (finished in 2012) and INCASS have among their goals the development of robotic platforms to automate as much as possible vessels' inspection processes (Eich et al., 2014). One of these robots is a micro-aerial vehicle fitted with cameras, which is in charge of collecting images that can provide the surveyor with a global overview of the different surfaces and structures of the vessel (Bonnin-Pascual et al., 2015). These images are intended to be processed afterwards to autonomously detect the defective areas.

Previous approaches on 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

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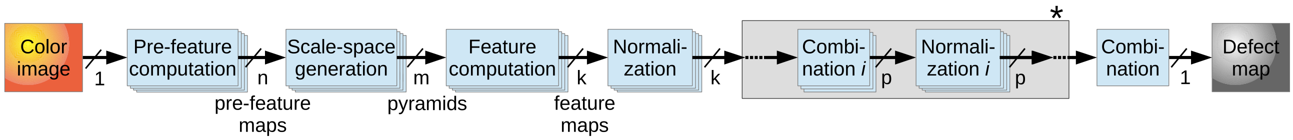

Fig. 1. Generic framework for defect detection. (⋆) means zero or more than zero instances of the corresponding stage.

conditions are controlled as well. Most 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. The short distance from which the images must be captured is another point in common among the majority of the algorithms. Furthermore, to provide good results, most of them require from a learning and/or parameter-tuning stages.

Special mention is made here to recent solutions based on Convolutional Neural Networks (CNNs), adopting latest deep learning training approaches. These techniques are widely used nowadays is many computer vision applications due to its high capacity of learning and their good performance in non-easy classification problems. By way of example, Oullette et al. (2004) and Zhang et al. (2016) describe methods based on CNNs for the detection of cracks, while the approach presented by Petricca et al. (2016) focuses on the detection of corrosion. As mentioned before, these machine learning techniques require from a previous training stage, which, in this case, involves a very large dataset.

Regarding defect detection over vessel structures, just a few contributions can be found. For example, Ozog and Eustice (2015) present a method to identify structural anomalies over visual reconstructions of underwater ship hulls. Restricting to those contributions which just use visual sensors, Bonnin-Pascual (2010) and Bonnin-Pascual and Ortiz (2014b) present detectors of cracks and corrosion for vessel structures. These algorithms do not need close-up images of the inspected surfaces to provide good results but their drawback is again that they require a previous training stage (e.g. to learn which is the color that corrosion usually presents) or tuning their working parameters (e.g. to know how thin and elongated must be a dark collection of pixels to be considered a crack), whose value is typically related with the distance from which the images have been collected.

To the best of our knowledge, only one method has been published for generic defect detection in vessel structure images (Bonnin-Pascual and Ortiz, 2014a). This approach makes use of a Bayesian framework to compute the probability of every pixel to correspond to some kind of defective situation. This probability is based on the information learned in a previous training stage.

This paper presents a novel approach for automatic detection of defects in images taken from the vessel structures. Unlike previous works, the presented approach does not require from tuning a large set of parameters nor performing a previous training stage. A framework is proposed as a generic classifier that can be configured to make use of different features, potentially leading to different defect detectors each. Furthermore, the framework foresees the combination of the respective feature responses in order to enhance the overall output quality. The conspicuousness of defects in general, together with the kind of defects that can be expected in metallic surfaces (i.e. cracks and corrosion) and the image capture conditions, have guided the feature selection process.

The rest of the paper is organized as follows: Section 2 describes the generic flexible defect detection framework; Section 3 explains how this framework particularizes for defect detection in vessel structures, considering contrast (3.1), symmetry (3.2) and three alternative combinations among them (3.3); Section 4 discusses on the results of some experiments; and Section 5 concludes the paper.

2. A flexible framework for defect detection

The importance of feature selection during the design of any classifier is discussed in Theodoridis and Koutroumbas (2006). In particular, the following questions must be answered: (1) which features are the best for a suitable classification, (2) how many features are necessary, and (3) how should these be combined to implement the best classifier.

Taking that into account, we oriented the design of our defect detector towards a flexible framework which allows an easy integration of different features and their combinations. To attain this level of flexibility, we considered that the framework must cover the following aspects: (1) it should allow computing one or more features that are potentially useful to discriminate between defective and non-defective situations; (2) final features response should not depend on scale; (3) one or more combination operators should be available to merge the information provided by the computed features and try to find the combination (if any) that improves the classification performance; and (4), related to the previous point, one o more normalization operators should be available to adapt the different features responses to a certain range, in order to ensure a proper combination.

This generic framework has been organized as a modular pipeline which involves different stages that can be configured (or even removed) depending on our needs, so that different configurations result into different defect detectors (see Fig. 1). Within the framework, each feature is computed as a different thread, while the final detection output results from the combination of the information supplied by all of them.

In more detail, the framework consists of the following stages:

- *Pre-feature computation.* The first stage prepares the input image to provide the information necessary to compute all features. From an input color image one can obtain, for example, the gray-scale (or intensity) image, the red channel image, the saturation image (from HSV color space), etc. Each one of these images is called a *pre-feature map*.
- *Scale-space generation.* This stage scales the pre-feature maps using a range of scale factors to obtain a collection of multiple-scale representations, also known as pyramids. The computation of each pyramid level can include filtering the input map using a specific kind of filter. One can compute, for example, a Gaussian pyramid which progressively low-pass filters and sub-samples the pre-feature map, an oriented Gabor pyramid for a preferred orientation θ, a simple sub-sampling pyramid computed without any filtering, etc.
- *Feature computation.* This is the core stage within the pipeline. Each instance of this stage is in charge of computing the value for a given feature for all the pixels of the input image. Since this can be fed with one or more multi-scale pyramids, a feature can be computed combining the information provided at different scales. Every output of this stage is called a *feature map*.
- *Normalization.* This step normalizes the different feature maps to the same range of values to enable their combination.