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Technical Paper

A deep learning approach for automatic identification of subsea events using AUV data

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Abstract

The use of deep learning in subsea inspection by Autonomous Underwater Vehicles (AUV) is a field that has a non-explored potential. Even though these vehicles operations are already automatized, their image analysis is still done manually, being a tedious job, passive of errors by distraction or exhaustion of the operator. This work develops a deep neural network to detect and locate events on subsea images captured by an AUV campaign. Typical subsea events consist of subsea pipeline track lines, pipeline crossing, presence of subsea valves and manifolds, presence of sacrificial anodes, etc. The final purpose of this study is to reduce the operational time and costs of those inspections by an automatic mapping of the sea floor. The results show the accuracy of the detection and the categorization as well as the efficiency of the geo-localization on a case study of mapping the crossing points (events) between several subsea pipelines.

Keywords: Autonomous Underwater Vehicle. Deep Learning. Subsea Inspection

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1. Introduction

Subsea systems are found in most oil and gas offshore fields in Brazil and the world showing their importance for the oil & gas industry. Those systems are essential to make possible the extraction of oil and gas from deepwater and ultra-deepwater fields. Because of their location at the seabed, difficulties in maintenance and inspection operations are faced by operators and service suppliers.

Inspections of the subsea systems are carried out by using Autonomous Underwater Vehicles (AUV). Those vehicles can achieve depths otherwise not achieved by human divers. Inspections using AUV are highly effective however the amount of data created requires lots of manpower to run the analysis and generate effective results, as the detection of significant events such as pipes crossings, presence of anodes or connectors.

Due to the high volume and complexity of the data, a great amount is underused or requires too much time to be analyzed, which prevents its application on the real-time operation. Therefore, the usage of artificial intelligence has great value because it raises the efficiency and speed of data processing enabling the operator to implement its outcomes to improve the operation.

The best artificial intelligence technique known so far for computational vision is Deep Learning. Among several uses of Deep Learning, one that has many appliances is computer vision. Industries based on automation, consumer markets, medical domains, defence and surveillance are most likely domains extensively using computer vision. Deep learning technology has achieved state-of-the-art results in the domain of image classification and object detection, Pathak, Pandey, Rautaray (2018).

Convolutional Neural Networks are part of Computer Vision's Deep Learning algorithms and it has achieved impressive performance with the GPU hardware deployment in recent years. The idea was proposed by Lecun et al. (1998) more than twenty years ago.

Even though Computer Vision has been used on the subsea field for a while, these authors could not find a paper that described an attempt to develop a crossing point detection algorithm using AI to inspect subsea pipelines. This makes room for the use of a Deep Learning algorithm that can identify this event underwater automatically.

In 2016, Bojarski et al. (2016) trained a convolutional neural network to map raw pixels from a single front-facing camera directly to car steering commands. Their system automatically learns internal representations of the necessary processing steps such as detecting useful road features with only the human steering angle as the training signal. Since then, many improvements have been made which makes the idea of self-driving cars a reality in just a few years.

On the underwater computer vision side, many kinds of research have been developed. In 2004 an algorithm was developed by Walther, Edgington and Koch (2004) to detect animals on images obtained by ROVs. Their algorithm worked well, with an error of only 6% when considering single frames only. For video processing, they got 70% accuracy when compared to manual analysis of the same data. Despite that, they did not use machine learning but only image processing.

On the subsea field, Kim, Yu and Yuh (2008) developed a study in which a neural network-based image processing algorithm was proposed for acoustic image classification used by Autonomous Underwater Vehicles. Even though the algorithm was properly developed, it was very limited and only recognized a few objects like cones, cubes and cylinders.

After extensive research on reputable sources of scientific papers, it can be seen that no research has yet developed a model capable of detecting subsea elements automatically, using deep learning algorithms trained by AUV inspection images.

This paper establishes the development of a convolutional neural network for the detection of crossings between subsea pipelines. The training and test sets of the neural network were selected from a dataset of AUV images taken during an inspection operation.

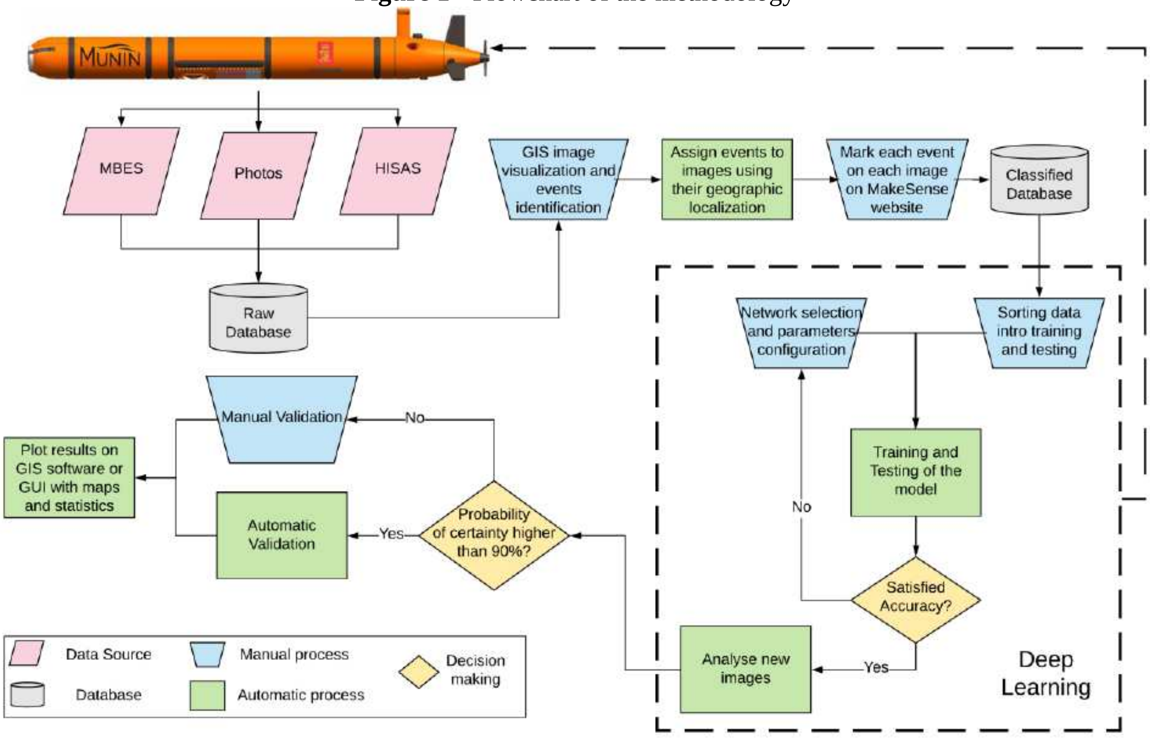
2. Methodology

The methodology of the whole process includes everything from acquiring data from an AUV trip to training the network and identifying events at new images. It can be divided into three steps:

- Building a raw database with data acquired from the AUV trip;
- Classifying and processing of the data with a manual validation of the events, training the network and checking its accuracy; and
- Identifying and geolocating new events by analyzing new images and displaying them on maps and GIS software.

A flowchart summing it up can be seen in Figure 1 and it will be explained in detail in the next chapters.

Figure 1 - Flowchart of the methodology



Source: produced by the authors.

AUVs contain several sensors to analyze their surroundings and collect data. Three of them are capable of capturing georeferenced images: Photos, HISAS and MBES. In this present work, only photos were used to identify crossing points.

Those photos are taken by the AUV camera that is capable of taking pictures of the seabed in scales of grey which can be analyzed later and identify events that can harm an oil field operation. These images are taken at a height of 4 meters from the seabed.

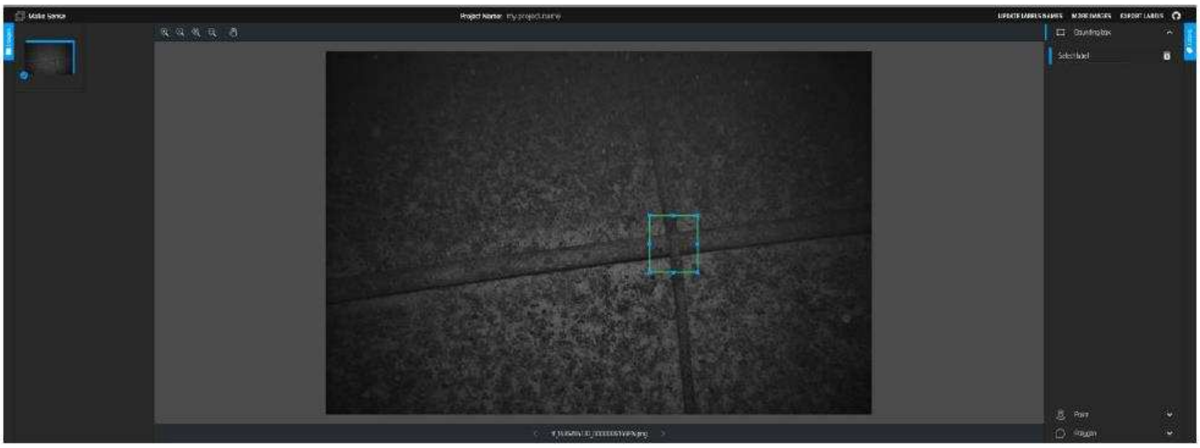
One of the main issues about underwater images is their low-quality and high-noise that pose great challenges for their analysis, just as described by Sun et al. (2018) below:

- Low illumination environments cause relatively low contrast background, which can confuse the traditional interest point detectors and produce weak descriptors.
- The object may appear to be of significantly different shapes over various camera angles due to the freely swimming environment.
- Most underwater pictures are of low resolution and low saturation, thus discriminative information is limited to recognize objects from the pictures.

Recently, some AUVs are capable of taking coloured photos. This is helpful when talking about the identification and classification of events in the environment like coral classification. For this work, the photos will be used to identify events on the pipelines and all of them will on a scale of grey.

To label the images containing events, and in particular, crossing points, the open-source website MakeSense (2019) was used. This was a manual task, labelling image by image, as shown in Figure 2.

Figure 2 - Example of image labelling on make sense website



Source: produced by the authors through make sense website

The Object Detection API created on Tensorflow by Google is already enough to be used directly with ordinary objects but for this work, changes and training are necessary, since new classes are under analysis. This is the step to be taken after labelling all images.

The images to be used on the network must contain a wide variety of shapes and conditions of each class. If you teach a network only by using similar images of a class, it won't show desirable results in the testing phase if the image to be tested is slightly different than the ones on the training phase. For example, for the crossing events, the more images containing different directions and the number of pipelines involved, the better. It is also important that the files be divided into sets. At least 70% of these files are used in the training phase.

Even though the images used in the training phase are completely new to the network, there is no need to train it from the beginning. It's possible to use pre-trained models with optimized weights, which will help decrease the training time and errors. For this paper, we used Faster R-CNN, Ren et al. (2016).

The testing data is used by the network to analyze its accuracy. The other 30% of the labelled images are used on each training iteration to determine its loss. The network is capable of calculating the error and making changes necessary to improve results in the next iteration.

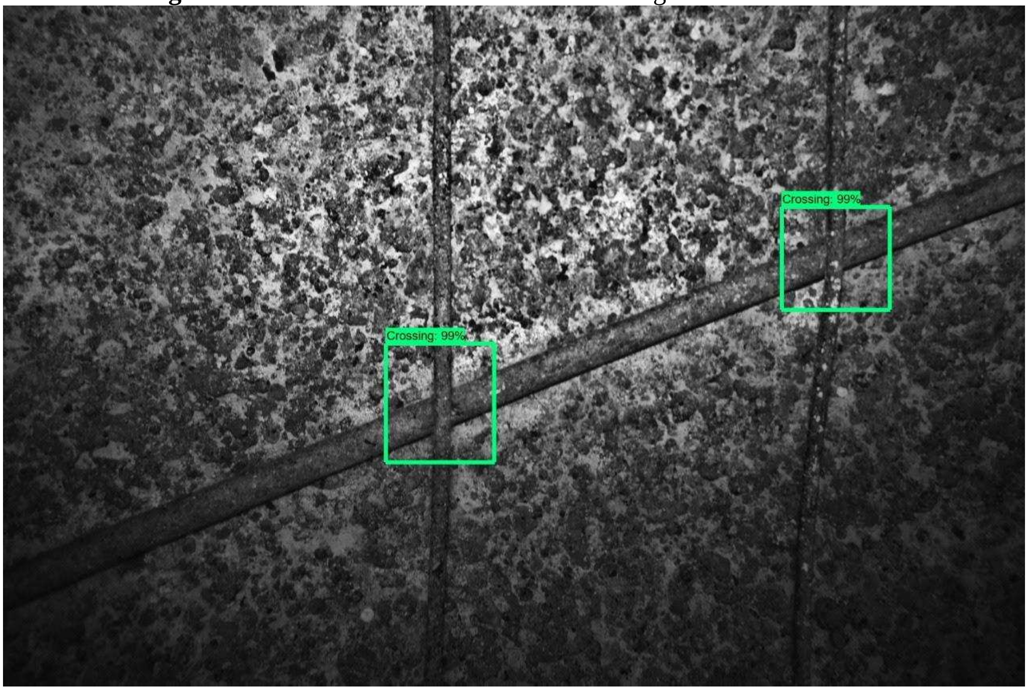
3. Results

For the training phase of the algorithm, 100 images were used for training and 43 for testing. The algorithm was then executed using ten new images never seen before by the network. An accuracy value of 100% was achieved, showing that this method is viable and requires minimal labour work with minimal data.

The training phase took about 8 hours in a computer with an i7 5500U @ 2.40GHz processor, 8 GB Single-Channel DDR3 RAM and Tensorflow CPU. It can be understood that more powerful hardware will be able to execute the algorithm much faster, allowing the network to be re-trained quickly every time more images are available or new events are identified and inserted.

It was expected that the network would be able to detect the events on the new images by itself and geolocate them by displaying their positions in a Geolocated Information File. An example of the results can be seen in Figure 3 and Figure 4 where the network correctly identified different crossings with 99% confidence. In Figure 5 and Figure 6, it can be seen the crossings geolocation.

Figure 3 - Result from event identification using IA network – case I

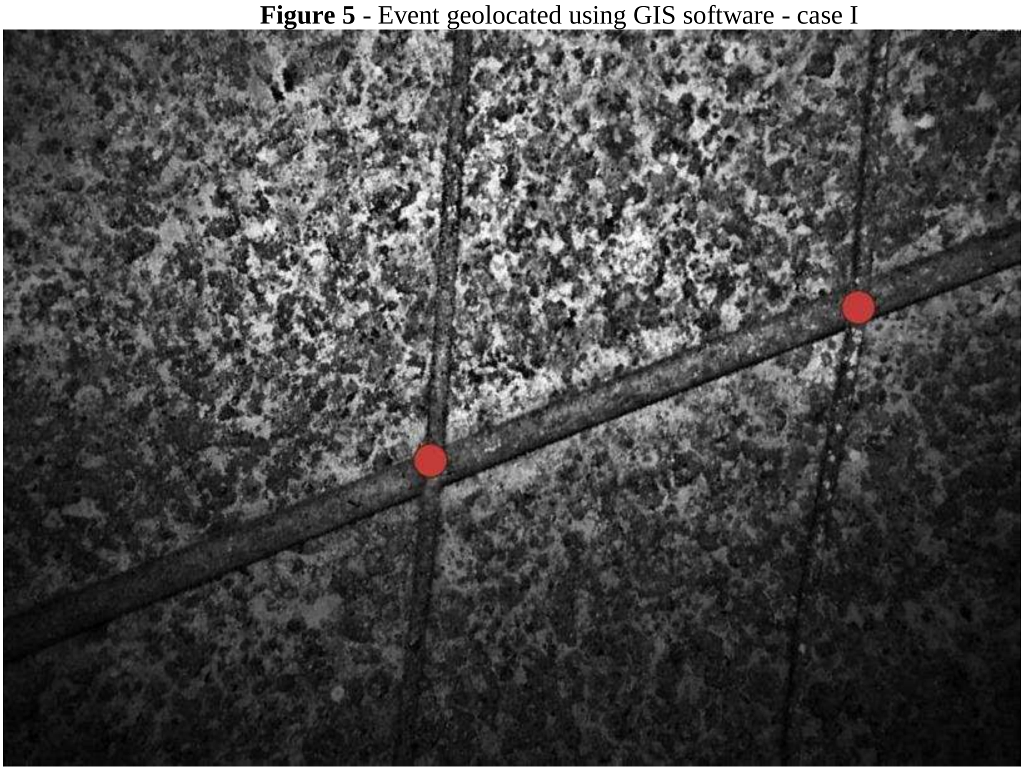


Source: produced by the authors from a confidential database

Figure 4 - Result from event identification using AI network – case II

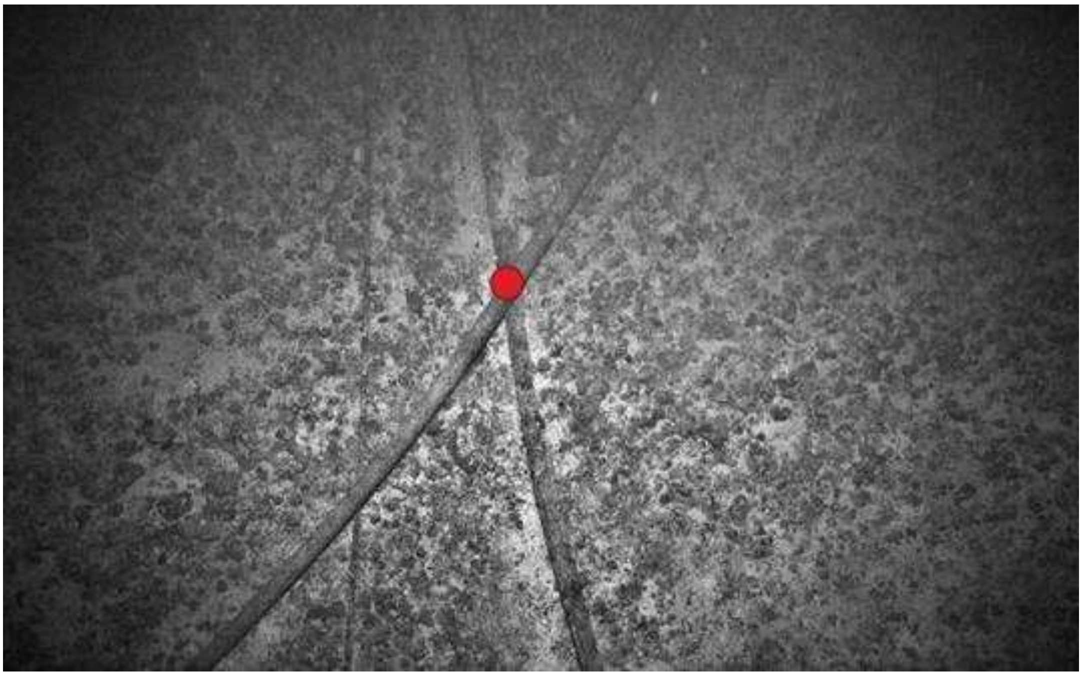
Source: produced by the authors from a confidential database

Figure 5 - Event geolocated using GIS software - case I



Source: produced by the authors from confidential database

Figure 6 - Event geolocated using GIS software - case I



Source: produced by the authors from a confidential database

4. Final Remarks

Detecting events on subsea pipelines can be costly and exhaustive when done manually. This operation can be improved with the application of Artificial Intelligence by training a Deep Learning Neural Network to identify these events by itself and display the results in a compressed and easy to read way.

Our network is capable of identifying crossing events with only a few hundred images used in training and can be scaled to identify new events when images are available.

To prevent the network from having low accuracy, the images set should contain a wide variety of shapes and conditions of each event, avoiding teaching the network with only similar images. So, re-training the network is important when new different images are available.

The next steps of this work are to re-train the network using images of new events, allowing it to identify all, or at least most of the events that can harm subsea pipelines.

When applied on AUVs to execute the analysis at real-time, our network can instantly warn the operator about a dangerous event and where it is located, resulting in an automatic mapping of the seafloor. Using this methodology, O&G operators could reduce their operational time and costs with inspection and even prevent errors caused by an employee's fatigue or distraction.

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