FULLY AUTOMATED SAR BASED OIL SPILL DETECTION USING YOLOV4

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ABSTRACT

The Eastern Mediterranean Sea is known as oil pollution hotspot because of high marine traffic and a growing number of oil and gas industrial activities inside, which makes efficient monitoring oil spills important in this area. Spaceborne Synthetic Aperture Radar (SAR) plays an important role for oil spill detection with its advantage of wide coverage and all-weather observations. However, discriminating whether the dark formations in the SAR imagery are from actual oil spills or look-alikes has been a challenging part. This study applied You Only Look Once version 4 (YOLOv4) object detection algorithm as an one-class (i.e. oil spill) object detector for learning oil spill features inside the Region of Interests (ROIs) and the background information from the rest of the image. The preliminary results pointed out that the pixel threshold for removing some tiny oil spills is suggested as they appeared regularly in the study area but are hardly visible. The average precisions (AP) of the trained model on validation and test sets are 67.80% and 65.37%, showing that the model is not overfitting on our training and validation sets. In addition, this study recommended some data augmentation strategies which might help improve the results.

***Index Terms*—** Synthetic Aperture Radar, Oil Spill Detection, Object Detection, YOLOv4, Deep Learning

1. INTRODUCTION

Oil pollution is one of the main sources of the marine contamination. Causes of the oil pollution could be separated into several different groups: operational discharge of oil from marine transportation, accidents at sea, oil and gas industrial activities, land-based sources, and natural seepage. Most of the large oil spills come from tanker accidents, while the operational oil spills from ships and offshore industries appear to be the main causes of oil pollution.The operational oil spills from ships include release of oily ballast water, tanker washing residues, fuel oil sludge, engine wastes, and foul bilge water. And the offshore petroleum hydrocarbons (e.g., crude oil and natural gas) exploration and exploitation not only produce toxic wastes but also increase the potential of fire and explosion accidents due to the flammable and explosive property of petroleum.

The Mediterranean Sea is surrounded by Southern Europe, Anatolia and North Africa, and it covers an area of approximately 2.5 million square kilometers. With the shortest route from Asia to Europe, the Mediterranean Sea is one of the seas has an extremely high traffic density with around 30% of the international merchant vessels crossing through and 20–25% of the oil tankers transiting [1]. The discoveries of large gas fields in the Levant Basin in the Eastern Mediterranean Sea in 2010 led to the increasing number of oil and gas industrial activities, which have raised the risk of oil leakage. Thus, this study focused on the oil spill detection in the Eastern Mediterranean Sea.

Spaceborne Synthetic Aperture Radar (SAR) has been widely used for oil spill detection due to its wide coverage and all-weather observations. European Maritime Safety Agency's CleanSeaNet oil spill monitoring service is an example of using satellite SAR image on preventing illegal oil discharges [2] The concept of detecting oil spill in SAR imagery is according to the dampening effect of oil slicks on the capillary waves that reduces the radar backscatter coefficient and causes dark formation in the image compared to the brightness of surrounding spill-free sea. The general procedures for oil spill detection using SAR imagery include dark spots segmentation, feature extraction and classification. Dark spots segmentation separates the dark formations from their background in the image, but some ocean and weather phenomena and biogenic films (e.g., algal blooms) also appear as dark spots in SAR imagery, which are called look-alikes. Therefore, feature extraction is then applied to obtain different features from oil spills and look-alikes. Finally, the classifier is used to distinguish whether the dark spot is an oil spill or a look-alike, which is the most challenging part in the whole detection chain. Recently, the Convolutional Neural Network techniques have been applied in feature extraction and classification to improve the determination of classes (i.e. oil spill or look-alike) [3].

The Eastern Mediterranean Sea, with nutrient sources from the coastal origin (e.g., increasing use of fertilizers for agriculture) and strong current system, is known as a hotspot for algal blooms [4]. As oil spills might appear inside algal blooms, learning the pattern of algal blooms is relatively

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important in this study. However, the segmentation step separates the dark spots from their background, at the same time discards the information of how oil spills look different from their surroundings, which is especially important in the case that oil spill is inside algal blooms. With the good performance on finding objects in the shadow and with insufficient light (see Figure 1), the object detection method might improve the oil spill detection by learning not only the features from the oil spills but also look-alikes appeared in the same images as background information. A previous study applies two-stage Convolutional Neural Network (CNN) based object detection technique to perform a coarse detection of the objects and to categorize the corresponding class (i.e., ship, coast or spill) for side-looking airborne radar (SLAR) imagery [5]. Another study based on the YOLOv2 one-stage object detector shows high performance on SAR images with the ship detection application [6]. This study aims to evaluate the possibilities of applying YOLOv4 object detection algorithm [7] on oil spill detection.

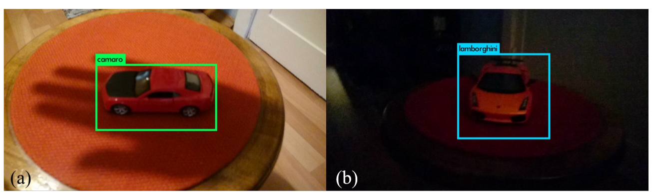


Fig. 1. YOLOv4 examples for car detection: (a) in the shadow and (b) with insufficient light [7].

2. METHODOLOGY

This study provided two tests for evaluating the potential of detecting oil spills with YOLOv4. Oil spills in different areas might have different patterns due to the difference in weather condition, current system, source of oil pollution and so on. Therefore, this study focused on the oil spills in the Eastern Mediterranean Sea, between latitudes 30–36°E and longitudes 31–34.7°N.

Figure 2 shows the processing workflow of this study. The Sentinel-1 SAR data was first pre-processed with the standard corrections, and the oil spills inside the pre-processed SAR results were labelled as oil objects. Then, the pre-processed SAR results were cropped into smaller scenes containing labelled oil objects with the size of $N \times N$ pixels, where N equals to the maximum of 640, object's width or object height's, in order to fit the input size of the training model. Finally, the cropped scenes with the labelled oil spill objects were used to train and fine tune the YOLOv4 object detector and evaluate the model performance. The trained models were evaluated by the comparison of their average precision (AP) on the test sets with the intersect over union (IoU) threshold equals to 50% [8].

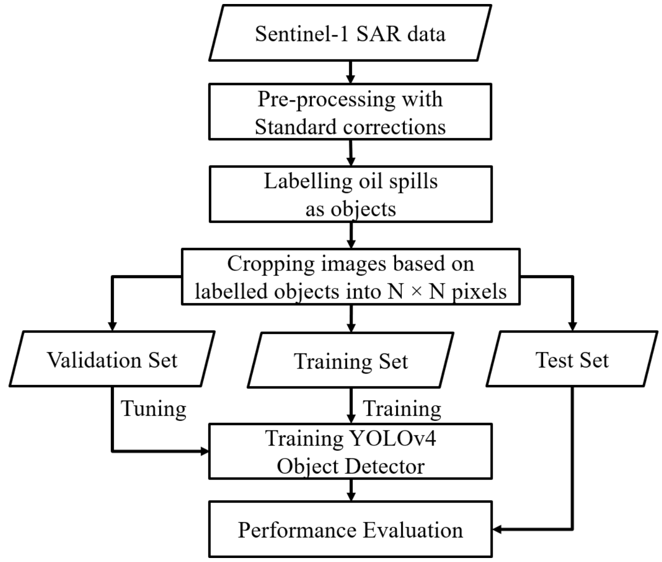


Fig. 2. The processing workflow of this study.

2.1. Dataset

The Sentinel SAR Level-1 Ground Range Detected (GRD) Interferometric Wide (IW) mode products covered the study area with 8915 scenes from January 2015 to July 2020. In the preliminary stage, only images from January 2015 to December 2017 with 3909 scenes in total were used. The Sentinel-1 SAR data was downloaded from Copernicus Open Access Hub. The SAR data was pre-processed with standard procedures, including border noise removal, thermal noise removal, calibration, ellipsoid correction and conversion to decibel. The resolution of the pre-processed SAR results is the same as the original products, which is around 20.5×22.5 m.

All the oil spills inside the pre-processed data were then manually labelled as objects by two trained persons with the class oil using LabelImg open source image annotation tool on GitHub [9]. Note that the look-alikes inside the images were not labelled, which then regarded as background information for the object detector. The objects in the bounding boxes less than 12500 pixels (i.e. 5 km^2) are categorised as small objects and the ones in the bounding boxes greater than or equal to 100000 pixels (i.e. 40 km^2) are categorised as large objects. The ones not belong to small or large objects are medium. The amount of labelled oil spill objects in different sizes are listed in Table 1. With a large number of labelled oil spill objects in the bounding boxes which are tiny, this study applied the first test to remove the hardly detectable objects by certain pixel thresholds.

The cropped images are then split into training, validation and test sets with the proportion of the amount of the objects at around 7:2:1, and the sizes of the objects were also following the same proportion. As there are strong seasonal precipitation and regular tropical-like cyclones in the Eastern Mediterranean Sea, the objects from different seasons are distributed into different sets.

Table 1. The amount and the percentage of oil objects with different sizes in the whole dataset from 2015–2017.

Category	size [pixels]	# Objects	%
Small	< 12500	7386	78.54
Medium	12500–100000	1439	15.30
Large	$>= 100000$	579	6.16

2.2. YOLOv4 Object Detection Algorithm

Deep learning based object detection algorithms generally contain feature extraction as the backbone and object localization and classification as the head. In addition, the neck is usually applied between these two parts for collecting feature maps from the backbone and passing them to the head. It is common to use a pre-trained model on a large labelled dataset (e.g., ImageNet) which has learned many features in advance in an object detection algorithm. However, a powerful network usually requires high computational resources. Enable to reduce the amount of computational resources but keep the performance of the network, Cross Stage Partial Network (CSPNet) partitions feature map of the base layer into two parts, one part goes through a dense block and a transition layer and then combines with the other part in the next stage [10].

For the head part, it is usually categorized into two-stage object detector and one-stage object detector. Two-stage object detectors first localize areas of the image that potentially contain an object, also known as regional proposal, the common techniques are sliding window approach and selective search. And the objects and their backgrounds in the ROIs are then classified into different classes in the second stage. On the other hand, one-stage object detectors use only one single deep neural network to localize and classify the object. They tend to be more efficient than two-stage detectors, but the accuracies are usually not as good as two-stage detectors. However, the accuracy and speed of the recent one-stage object detector YOLOv4 [7] have been well improved by its new architecture of the backbone, the modifications of the neck and the applications of Bag-of-Freebies and Bag-of-Specials during the detector training. YOLOv4 updated its backbone from Darknet53 to CSPDarknet53 based on the concept of CSPNet [10], which enhances the learning capability of the network. A new method of data augmentation, Mosaic, is introduced in YOLOv4, it mixes different training images to increase the variance of background of a certain object class. This study provided the second test for finding the suitable data augmentation parameters for our study.

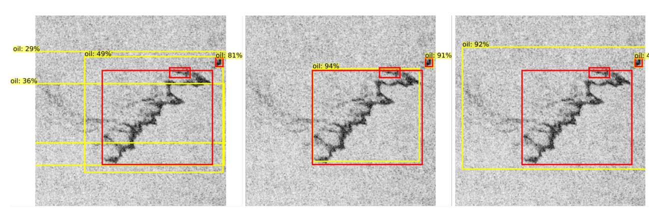
3. PRELIMINARY RESULTS

There are regular small oil spills in the Eastern Mediterranean Sea (see Table 1); however, there are hardly detectable for the model. In addition, our main focus is on detecting the larger oil spills which might influence more wildlife in a larger area. Test 1 compared the model performance on removing tiny oil spills with different pixel thresholds.

The case "all" used all the images inside the dataset and the case "rm_small_28" and "rm_small_48" removed some images in which the bounding box of the object has the size smaller than $n \times n$ pixels or the length of any side smaller than n pixels from the dataset, n equals to 28 and 48, respectively. Table 2 shows the amount of objects that are use in different cases and their AP on the validation set and test set with the IoU threshold equals to 50%. Figure 3 shows one test image detected by the three different trained models. Table 2 shows that the case "all" and "rm_small_48" have similar AP on validation set, but the former seems to have some abundant predictions which are not precise on Figure 3. The results indicate that the pixel threshold of 28 is suggested. Moreover, the AP of the case "rm_small_28" on validation and test sets are 67.80% and 65.37%, respectively. The two numbers are really similar, which confirms that the model is not overfitting on training and validation sets.

Table 2. The amount of objects for different cases that were used in Test 1, along with the AP of the trained models on validation set and test set.

Case	# Objects (train/val/test sets)	AP@IoU=0.5 [%] (val set)	(test set)
all	6558 / 1879 / 967	62.65	59.47
rm_small_28	3512 / 1010 / 511	67.80	65.37
rm_small_48	2434 / 694 / 353	62.25	61.32



(a) all (b) rm_small_28 (c) rm_small_48

Fig. 3. Example of the prediction by different trained model from Test 1. The yellow bounding boxes show the predicted oil spill objects from the trained YOLOv4 model with the confidence scores. The red bounding boxes are the ground truth oil spill objects.

This study applied the Test2 for trying different data augmentations, the cases “aug1”, “agu2” and “aug3”. The only difference between the case “aug1” and the case “aug2” is if the rotation is on or not. The case “aug3” increased the colour parameters, such as saturation, exposure and hue. Table 3 shows the AP on the validation set and test set with the IoU threshold equals to 50%. From the AP on validation set, the case “aug1” seems to perform better than the others. The idea of applying data augmentation is to increase the amount of data by applying slightly modifications from the original dataset. According to the AP on test set, comparing the case “aug1” and the case “aug2”, adding rotation to the data augmentation seems to be not helpful with the model performance. The possible reason might be that lots of small oil spills in our dataset are close to the round shape. Therefore, applying rotation might increase the possibility of model overfitting on the small oil spills, but it might help to detect complicated shaped larger oil spills in this study.

Table 3. The AP of the trained models on validation set and test set from Test 2.

Case	**AP@IoU=0.5 [%]** (val set)	**AP@IoU=0.5 [%]** (test set)
aug1	73.56	58.67
aug2	71.68	58.78
aug3	72.90	57.00

4. CONCLUSION

This study has applied two preliminary tests for oil spill detection with satellite SAR imagery based on YOLOv4 object detection algorithm. Test 1 shows that the removal of some tiny objects is suggested as some of the objects are hardly detectable by the model, and the pixel thresholds of 28 is preferred in this study. The APs on the validation and test sets are 67.80% and 65.37%, showing that the model is not overfitting on the dataset. Test 2 indicates that the different data augmentations which has applied in this study did not have significant difference on the performance. And applying the rotation for data augmentation might cause overfitting due to the large amount of nearly round shape small oil spills objects in our dataset. But apart from small oil spills which appeared to be round in shape, lots of larger oil spills are with complicated shape. In addition, the medium and large oil spills are only around 20% in our dataset. Therefore, it is suggested to apply data augmentation focusing on medium and large oil spill objects to improve the object detector. With the experience from the preliminary tests, an improving object detection model and its extensive evaluation of performance are foreseen in the near future.

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