Integration of a Deep Learning Based Oil Spill Detection System into an Early Warning System for the Southeastern Mediterranean Sea

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Abstract

Deep learning based techniques have been applied in different environmental monitoring applications, including oil spill detection. This study aims to provide an oil spill detection and early warning system in order to take quick action for clean up operations for minimizing the environmental impact. Oil spills in the spaceborne Sentinel-1 Synthetic Aperture Radar (SAR) data are detected by a trained deep learning based object detector. The detections are then defined as binary masks by the segmentation method. Afterwards, the slick trajectory simulation is carried out. The system is running automatically on a regular basis when there are expected Sentinel-1 acquisitions. However, to avoid unnecessary clean up operations on false alarms, the system requires manual confirmation before sending a warning to the corresponding decision makers. The system performance should be evaluated with detailed analysis, but the feasibility of building such an automated oil spill detection and early warning system has been shown.

I. Introduction

Marine oil pollution from maritime accidents and illegal human-caused oil discharges can pose a great risk of environmental damage and have large-scale and long-term biological consequences. As an oil spill begins to weather and disintegrate into small fragments, it becomes difficult to recover the oil. Therefore, it is important to take action early to limit the spread of oil spills and predict their trajectory, which highlights the necessity of building an early surveillance system. With the advantages of wide coverage and frequent revisit, spaceborne SAR has been widely used in different environmental monitoring applications including oil spill detection. Oil spills appear as dark formations in SAR images as they dampen the gravity-capillary waves and thus reduce the backscatter. However, other phenomena also appear as dark formations (also known as look-alikes), which makes automated detection of oil spills challenging. Based on the large amount of accessible SAR data after the advent of Sentinel-1, a previous study highlights the possibility of detecting oil spills with a deep learning based object detection algorithm [1]. With this previous experience, this study aims to provide an automated oil spill detection system which targets oil spills in the Southeastern Mediterranean Sea on a regular basis. The detections are handed off to an existing oil spill trajectory simulator for predicting the influenced regions over time. The integration of the different parts into a complete early warning system can help with the oil combating response.

II. Methodology

This study focuses on oil spills in the Southeastern Mediterranean Sea within longitudes 31.5–36°E and latitudes 31–33.7°N. The overall structure of the proposed oil spill detection and early warning system is shown in Figure 1. The system includes four subsystems: satellite data processing, oil spill detection, forecast of synoptic condition and oil trajectory simulation. In the satellite data processing subsystem, Sentinel-1 SAR Level-1 Ground Range Detected (GRD) products are downloaded from Copernicus Open Access Hub on a regular basis and preprocessed with a series of corrections automatically with the use of Sentinel Application Platform (SNAP) Python API. Afterwards, a mosaic of latest preprocessed scenes covering the study area is formed and sent to the oil spill detection subsystem.

In the training stage of the oil spill detection subsystem, different scenarios were carried out to train the deep learning based You Only Look Once version 4 (YOLOv4) object detection algorithm [2] on detecting one-class (i.e. oil spill) objects. In the detection stage, the trained detector targets oil spills inside mosaics and defines their positions by bounding boxes. In order to obtain the exact areas covered by the respective oil spills, segmentation is applied. The output binary masks are handed off to the oil trajectory simulation subsystem. The simulation of oil spill trajectory and fate requires oil spill incident detail and forecasts of synoptic conditions, such as wind, sea current and sea water temperature. The MEDSLIK model [3] then simulates physical processes of oil spill incidents with respect to evaporation, diffusion, dispersion, emulsification, and beaching. The simulation results are available via an online interface enabling users to perform their own simulations and visualize the results.

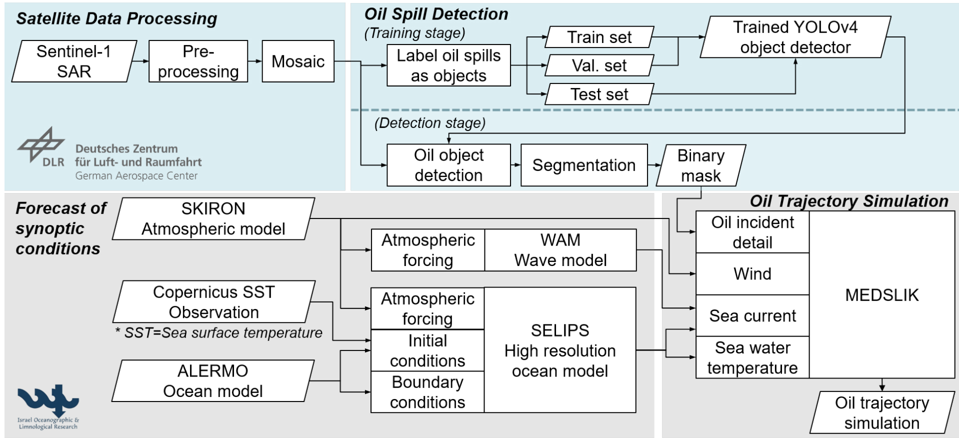
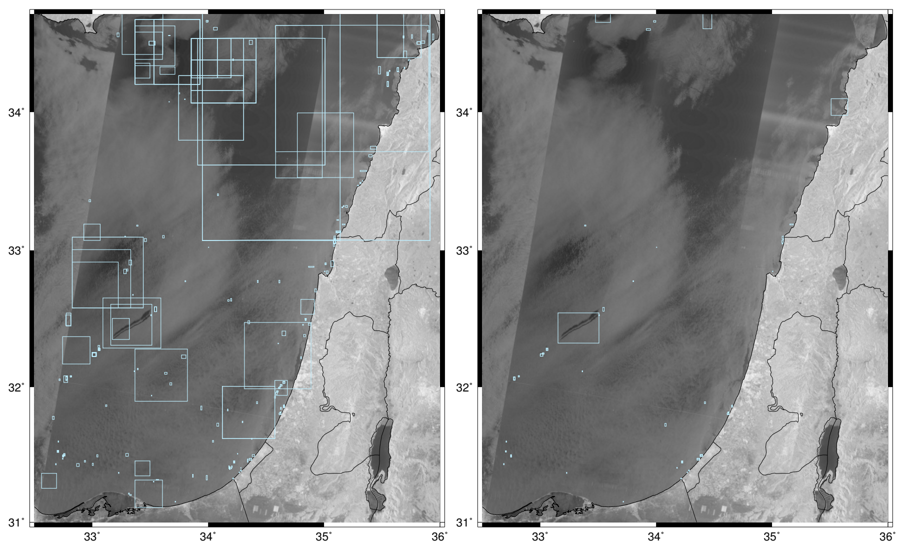


Fig. 1. An overview of the purposed oil spill detection and early warning system.



(a) (b)

Fig. 2. An example of detections from the oil spill detection subsystem using (a) the trained detector from the previous study [1] and (b) the implemented detector.

The satellite data processing and oil spill detection subsystems are developed and maintained by DLR. The forecast of synoptic winds is provided by the SKIRON system from the university of Athens, and the forecasts of sea currents and waves are performed by IOLR. The oil trajectory simulation subsystem and its connected user interface are maintained by IOLR.

III. Results

In the previous study, 9768 oil spills were used to train a YOLOv4 object detector. It reached an average precision (AP) of $69.10\,\%$ and $68.69\,\%$ on the validation and test sets, respectively [1]. This showed the ability of finding oil spills from the given image patches and highlighted the possibility of building an efficient oil spill detection system on regular SAR acquisitions based on the trained detector.

To illustrate how oil spills are detected in the oil spill detection subsystem, a selected case at 03:43 on 24 June 2019, with not only oil spills but also some other phenomena which appeared as dark formations, is used in the following. Figure 2(a) shows the detections from the trained detector. However, there are lots of false alarms. As all the image patches used for training the object detector include at least one oil spill, look-alikes were only learned as background information by the detector when they were near oil spills. Therefore, to further improve the detector, image patches without oil spills, but look-alikes or other remarkable features, were included in the training. Note that these image patches were not given any annotation and therefore considered as background. Figure 2(b) shows great improvement on avoiding the detection of look-alikes by the improved detector. Such an improved detector is applied in the oil spill detection subsystem running on a regular basis.

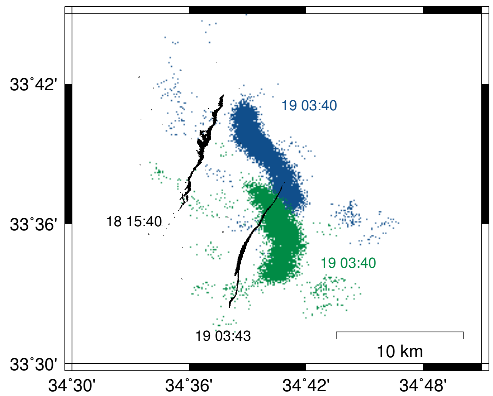


Fig. 3. An example of oil spill detections in consecutive Sentinel-1 SAR data at 15:40 on 18 August 2022 and at 03:43 on the next day (in black). With the second observation from Sentinel-1, additional information could be provided to validate and correct the trajectory forecast. The trajectory of the original simulation for 12 hours after the first observation is displayed in blue, and the corrected one is shown in green.

After the oil spills are detected, they are segmented into binary masks and delivered to the MEDSLIK model for trajectory simulation. It uses daily forecasts of synoptic conditions and generates hourly estimation of the slick trajectory. The trajectory simulation shows users the possible areas influenced by oil spills in the next few days. In some cases, the revisit time is short enough so that consecutive passes detect the same oil spill at different stages of its trajectory. In these cases, the new detection can be easily attributed by the users to the older detection and they may use the new information to validate the trajectory forecast. The system also provides an option to correct the simulation with the new location. This can be done internally in MEDSLIK, which adds a velocity modification computed from the displacement vector between the centroid of the new observation and the corresponding location in the original simulation. Alternatively, the system can search by external iteration for the optimal velocity modification. This is suitable when the spatial variation of the velocity (e.g. strong shear, circulation around bays or islands) makes the internal correction method inaccurate. As an example, Figure 4 illustrates a user-made simulation with internal MEDSLIK correction based on the new observation. The black oil spill binary masks shows the observations from Sentinel-1 at 15:40 on 18 August 2022 and the consecutive observation after 12 hours. The unmodified velocity in the original simulation (in blue) was westward with shear such that there is stronger velocity at the south of the slick. The corrected simulation (in green) pushed the slick southwest towards the observation. However, the resulting shear caused incorrect deformation of the slick.

IV. Conclusion

An automated and operational oil spill detection system was demonstrated and integrated into an early warning system in the Southeastern Mediterranean Sea for minimizing the environmental impact of oil spill events. The whole system is currently operating on a regular basis, which helps reduce the time spent on manual check and annotation. Based on the estimated slick trajectory, further information, which is often needed for large oil spills but not derivable from SAR, such as oil type and oil thickness, can be gathered with different sensors. Afterwards, strategies for combating the oil slicks can be developed according to oil type, sea state, the habitats of the influenced regions, available response resources, and so on. To avoid false alarms, the system requires manual confirmation before sending a warning to the corresponding decision makers. Further detailed analysis on performance regarding detectability, false alarm rate and accuracy of the numerical forecasting is required, but the feasibility of building an automated oil spill detection system is shown. Continuous tracking of small slicks can be used in future studies, to deduce velocities which will be assimilated back to correct the circulation model. Furthermore, with the experience of building such a system for the Southeastern Mediterranean Sea, extending the study area to global oil spill hotspots is foreseen.

Acknowledgements

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