Towards Automatic Detection of Dark Features in the Barents Sea using Synthetic Aperture Radar

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Abstract—Increased human presence and commercial activities in the Barents Sea (fishing, offshore oil and gas exploration) are amplifying the need for large-scale operational ocean monitoring of the eventual oil spills in the region. The geographical location and climate impose additional constraints on satellite-based monitoring, making it necessary to use Synthetic Aperture Radar (SAR). Dark features or low backscatter areas are frequent within the SAR images and their occurrence may indicate oil spills or so-called lookalikes. Automatic oil spill detection hinges on accurate separation of the lookalikes from actual oil spills. Two main types exist in the Barents Sea: newly formed sea ice and low wind regions, where the former occur during the freezing part of the year (approx. November - April) and the other year around. Mapping the occurrence of oil spills and lookalikes in the Barents Sea on a seasonal basis would add to our understanding and knowledge of the low backscatter phenomena. Awareness of the major locations of oil spills, natural oil seeps, or lookalikes, are important for operational services and their effort to reduce false alarms. Here, we explore the use of a segmentation-based dark feature detection method with Sentinel-1 Extra Wide-Swath SAR images. We test the method on images acquired over the Barents Sea during the freezing season, and cross-validate the results with two sets of dark features segmented by operational expert oil spill and sea ice monitoring services. The results are discussed, together with currently developing method improvements, all while working towards a fully-automated method for monitoring dark features in the Barents Sea.

Index Terms—Oil slicks, newly formed sea ice, SAR, polarimetry, Arctic

I. INTRODUCTION

ARK features in Synthetic Aperture Radar (SAR) constitute signatures of low backscatter areas of various shapes, extents and origins. Within the Arctic ocean, a common dark feature is represented by the thinnest ice types including new ice, nilas, and young ice [1], but also e.g., oil slicks (mineral or animal) and low wind regions. Oil slicks are more common along the commercial shipping routes or in the vicinity of oil and gas platforms in the Barents Sea [2], whereas new ice formation takes place in, e.g., the marginal ice zone (MIZ) and leads [3]. Newly formed sea ice and leads provide safe routing for ship traffic and cost-effective passage through the sea ice, therefore oil slicks may occur in their vicinity. Advanced Microwave Scanning Radiometer 2 (AMSR2) data was used to identify the peak in new ice formation for the Barents and Kara Seas as occurring between October and February, though with large inter-annual variations [3]. In the context of operational monitoring, using the finer resolution SAR could enhance the detection of dark features with potentially small dimensions and irregular shapes.

SAR satellite images have a long history of being used for operational surveillance of ocean areas, detection of marine oil slicks and classification of sea ice types. This is possible thanks to the nature of radar imaging, which is independent of natural light or cloud cover. The spatial coverage and the temporal resolution (twice daily coverage of the Extra Wide (EW) mode in the HH/HV configuration over the Arctic Ocean) offered by Sentinel-1 as well as the free data policy makes it the obvious SAR data source. This paper presents an automatic method for the detection of dark features in Sentinel-1 EW imagery. The method consists in selecting segments with low backscatter produced by a segmentation algorithm based on statistical mixtures [4] [5].

In the EW mode, data is acquired under a range of incidence angles spanning over approx. 28°, which implies considerable intensity decay from near to far range [6] [7]. The segmentation algorithm merges theoretical aspects and empirical observations into a statistical model that accounts for the decay by assuming non-stationary per-segment means [5]. This ensures that the dark features are encapsulated within the same segments. In order to demonstrate the performance of our method, we have selected two Sentinel-1 EW images acquired in the Barents Sea and containing dark features that extend throughout the range. The automatically segmented dark features are also compared with a set of manually segmented dark features provided by operational oil spill detection services at ScanEx Moscow, as well as with sea ice classifications with specific emphasis on new ice types carried out by experts at the Norwegian Ice Service.

The main purpose of this study is to demonstrate the ability of the proposed method to identify dark features. The long term objective is to work towards identifying the locations and times of the year where dark features are most pronounced. In order to accomplish this, a thorough assessment of a larger dataset will be required and constitutes ongoing work.

II. METHOD

Our proposed dark feature detection method is automatic and consists of a segmentation step and a dark feature selection step.
Moreover, the overlap between the automatically and manually

V. Preliminary Results and Discussion

Fig. 1 shows the two original Sentinel-1 scenes (a and c), as well as the dark features identified by our method and overlapping validation data (b and d).

Scene #1 contains newly formed sea ice with varying levels of brightness, as the smooth regions show up as dark, while the more rough, fragmented regions as slightly brighter. The automatically identified segments contain only the darkest regions, while the manually delineated segments from dataset 1 also incorporate the brighter parts considered by the experts as part of the dark feature. Therefore, some differences stem
Fig. 1. The two Sentinel-1 EW images (HH Intensities in dB) and identified dark features. The left column shows the Sentinel-1 images #1 (a) and #2 (c) and the right column (#1 (b) and #2 (d)) shows the identified dark features. Automatically identified dark feature segments are shown in blue, validation dataset 1 is represented by red outlines and validation dataset 2 by the bright yellow areas.

from the slightly different definitions of the dark features, and may be eliminated by adding a segment fusion step. The visual expert opinion is furthermore supported by the sea ice validation dataset (dataset 2), which outlines the likely new ice formation region. The automatic segments are also covered by dataset 2, with the exception of a few dark areas on the southern tip of Novaya Zemlya. The discrepancy highlights the importance of secondary analysis of the automatically obtained segments, which may include a manual step for the removal of some areas. As an alternative, it is worth exploring the use of complementary information from the cross-polarized channel for the exclusion of areas that may be incorrectly included in the dark feature segment.

Scene #2 is more complex due to the presence of low backscatter regions representing both freezeup areas and low wind areas. The latter can be seen in the central part of the scene, and was confirmed by SST data used in dataset 2, where the temperatures were too high to support new ice formation. In the western extremity of the scene, we can observe a dark feature that was not detected by the segmentation algorithm. This is likely due to the positioning of the feature in the far range, where intensity values are approaching the noise floor and the reliability of the segments decreases. Additional differences between the automatically and manually determined segments are, as in the first scene, determined by variations in backscatter intensities within the dark features.

A quantitative comparison was performed between the au-
automatically and manually obtained segments by considering the latter as reference. The automatically detected segments were found to overlap with 56% of the reference for scene 1, respectively 48% for scene 2. Additional steps will be required for a more precise detection. However, considering that the contours of the dark areas are very well determined, even a semi-automatic approach would be superior to a full-on manual approach.

VI. Conclusions and Future Work

The proposed method is able to identify dark features across an entire wide-swath SAR image, thereby ensuring that dark features covering different incidence angles are combined into one coherent segment within each image. The qualitative comparison with manually selected dark features shows that the overlap is generally good and the segment outlines are well determined. The discrepancies observed in both the qualitative and quantitative analysis may be diminished by adding a manual step to the method, or by exploring algorithm improvements. One such improvement is currently being developed and consists in the integration of a variable noise-floor model for the mean of the intensity distribution, in order to reduce errors originating from noise artefacts. This will also allow the use of the cross-polarized channel as complementary data. Moreover, segment selection was performed here in a very simplistic way, and segment fusion could be a better option if the dark features are defined as including variable intensity levels. Lastly, our analysis suggests that the integration of, e.g., CMEMS SST products into the method may ensure the separation of low wind areas from the other dark features.

ACKNOWLEDGMENT

This research is financed by CIRFA (RCN Grant no. 237906), OIBSAR (RCN Grant no. 280616), and the Russian Foundation for Basic Research under grants No.18-55-20010. The Sentinel-1 data was provided through Copernicus and processed by ESA.

REFERENCES


