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## A Survey on Discrimination of Oil Spill from Biogenic Silks under Low Wind Atmosphere by SAR Images

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**ABSTRACT:** Oil spill is a major natural disaster in marine environment. Oil spill detection is a hectic process. Now a day, SAR is preferred to find out the oil spill in order to achieve better result. In this survey paper, the techniques which are used to mitigate some common limitations in SAR-based oil spill detection are analysed. Some of the limitations are taken into consideration. First, the technique used to distinguish oil spills from other look-alikes like biogenic silks are explored. Second, the analysis of algorithm to minimize the variations due to wind and waves.

**KEYWORDS :** SAR , Biogenic Silks, ANN, Expectation Maximization of Gaussian Mixture Models

### I. INTRODUCTION

Most of oil spill detection algorithms using SAR data usually consider “soft data” and the dark features visible on the SAR images have usually not been taken into consideration. So it often leads to misclassifications. Since a key challenge in oil spill detection by radar is the discrimination between oil films and biogenic or monomolecular slicks. Conventional methods to discriminate between them are based on the difference in 1) the reduction of the Normalized Radar Cross Section, 2) position and shape, and 3) texture etc. In general, position and shape are best suited for discrimination. However, in many cases the radar signatures of both types of surface films are quite similar, which often gives rise to misclassifications (Werner Alpers., 2017). Success in detecting oil spills in the SAR images mostly relies on where a feature is located within swath. The observed NRCS values in SAR image is affected due to the wind direction relative to the SAR view. The wind speed variability also detected by SAR images. SAR images provide a very wide view of the high variability of atmospheric meso-scale and sub mesoscale processes at the marine boundary layer because atmospheric wind stress produces and modulates the Bragg waves. The low-backscatter occurs due to areas of relatively low wind speed. Atmospheric gravity waves (AGW) and boundary-layer rolls produce distinctive quasi- periodic dark (low wind speed) and bright (high wind speed) patterns in SAR images. Areas of wind shadowing or other obstacles are also commonly imaged by SAR.

Oil films on the sea surface damp the capillary waves and smooth the roughness of the water surface. These differences in backscatter signals from the water surface allow the radar to detect oil pollution. Despite the numerous advantages of radar images, however, there are still a number of limitations that cause the identification of oil spills to be difficult or impossible. Thus, the basic conditions for successful detection of oil on the sea surface are the wind conditions.

When wind conditions of up to 2.5 m/s exist, a calm zone is formed, and the oil slick is drained from the water surface. Conversely, in wind speeds greater than 12 m/s oil slicks mix with water. In both cases, identification is not possible (Fig.1). The most optimal conditions are wind speeds of 3–8 m/s, when the oil is clearly seen on the radar image as dark patches on a bright background water surface (Ivanov and Zatyagalova [2007](#); Kamagate [2011](#)).

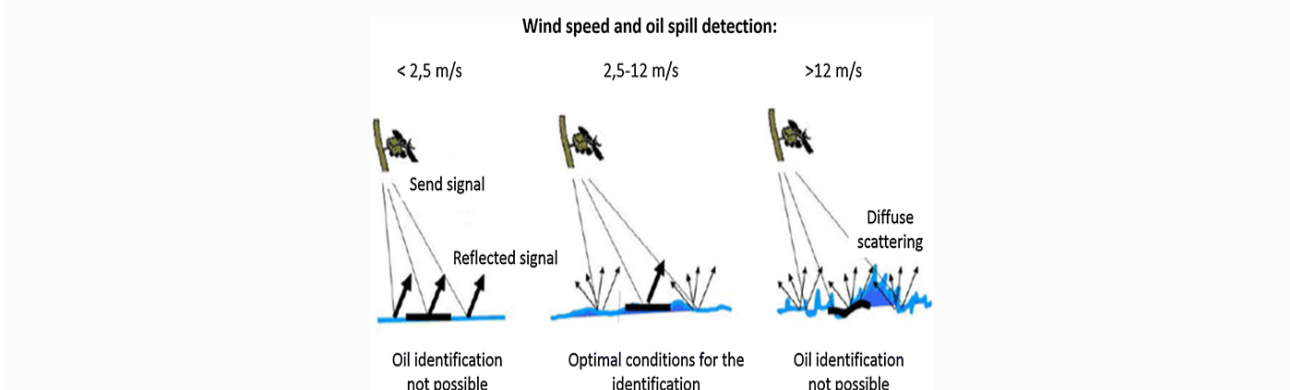
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The area under consideration is characterized by wind speed of 5–8 m/s, which are the most favorable conditions for the detection of oil slicks.



SAR and optical method are the two methods used in oil spill detection. Remote sensing is best suited and an effective method to detect oil spills. Among satellite sensors, the optical technique is incredibly effective in detecting work oil floating below ocean surface in terms of the changes of wavelength and sea surface reflection factor (Otremba, 2016). The most important factors influencing the performance are the wind and wave height. At sea level, the components of weather are its speed and wave length. Wind is the component which generates waves and also changes the rate of surface drift of oil.

## II. BIOGENIC SLICKS

Sea surface coverage with biogenic surface films, also called biogenic slicks, is a ubiquitous phenomenon in the World's ocean and is greater than previously thought (Wurl et al., 2011, 2016). Biogenic slicks are caused by cyanobacteria algal blooms (harmful algal blooms) which can be often found in sea areas and lakes subject to excessive inflow of industrial or agricultural waste water (Wang et al., 2017).

Biogenic surface films can be encountered on the sea surface only in the form of monolayers, which means only one molecular layer thick (typically 2.4–2.7 nm). They consist of surface active material (or surfactants) secreted by biota in the water column, including phytoplankton and fish, generally located in the water column below the wave-stirred water layer (Wurl et al., 2016; Kurata et al., 2016).

## III. DIFFERENT METHODS TO DISTINGUISH BIOGENIC SLICKS FROM OIL SPILL

Synthetic aperture radar (SAR) has been used often to detect oil-spill areas through the backscattering intensity difference between oil and background pixels. To detect large-scale oil spill areas in SAR images effectively by focusing on optimizing the input layer to artificial neural network (ANN) through removal of the factor of lowering the accuracy. An ANN algorithm was used to generate probability maps of oil spills. By applying a non-local (NL) means filter and median filter to the input neurons for ANN, highly accurate pixel-based data processing was conducted through false or un-detection element reduction. In addition, the standard deviation of co-polarized phase difference (CPD) was used to reduce false detection from the look-alike with weak damping effect. The algorithm was used in TerraSAR-X images of an oil spill caused by stranded oil tanker Volganefti-139 in the Kerch Strait in 2007 and effectively validated. With this validation results of the receiver operating characteristic (ROC) curve, the oil spill was detected with an associated accuracy of concerning ninety five percentage and false detection by look-alike and speckle noise was greatly reduced (Daeseong Kim., 2018).

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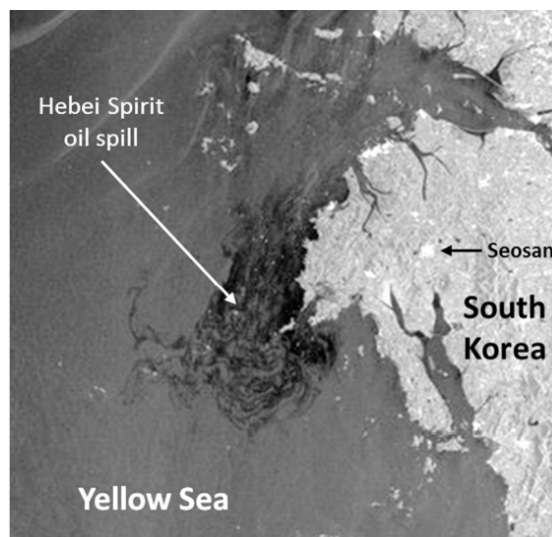
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It was difficult to distinguish between different type of oil slicks and from similar look-alikes due to the similarity of their radar backscatter signals. To face this challenge, polarimetric SAR data is used to derive the polarimetric parameters which detects certain features from physical properties of the scatterers on the sea surface. Some of these options area unit wont to sight oil spills victimisation Expectation Maximization of Gaussian Mixture Models. This method is comparatively performed well for RISAT-1 dataset from TerraSAR-X dataset. The strongest factor for incorrect results is found to be the high sea waves caused due to high wind speeds. Mostly, the shadows created by the high surface gravity waves are misclassified. The slick areas extracted under this method helps in finding that the stretching of the mineral oil slicks is in the direction of wind and its extent is also proportional to the quantity of oil within the slicks. The extracted slick areas are then used to compare the polarimetric features on the basis of their potential to separate oil slicks from water and from other oil slicks. Oil-water and oil-oil class are distinguished using determinant of the covariance matrix. Mostly, a covariance matrix based Wishart maximum likelihood classifier (W-MLC) is chosen for oil spill classification. The results of this classification are found to be much better than Gaussian based MLC, with no misclassification in the near range and a gain in overall classification accuracy of 16-34% (ANURAG KULSHRESTHA., 2018).

Graph-based visual saliency model is used to extract bottom-up saliency features such as the regions with high visual saliency object in the ocean. For top-down saliency, a seperate model called Spectral similarity match model was used to distinguish oil regions and exclude the other salient interference by spectrums. The regions containing oil spills were found using these complementary saliency detection steps. Then, the genetic neural network was wont to complete the image classification ( Ying Li., 2017).



**Figure 1 SAR image acquired by the ASAR onboard the Envisat satellite on 11 December. The oil film has broken up into patches and has probably formed emulsions.**

Mineral oil form connected oil films immediately after spillage, but then, after some time, they break into patches as shown in Fig. 2. This SAR image was acquired over the Yellow Sea after 5 days and a large amount of crude oil was spilled from a tanker in collision with another ship (Kim et al., 2015). The oil spread to the south due to the action of the wind and currents (mainly tidal currents). Like surface active material of biological origin, also mineral oil can be entrained by surface currents. Thus, we conclude that also texture cannot always be used as a reliable indicator for discriminating between mineral oil films and biogenic slicks.

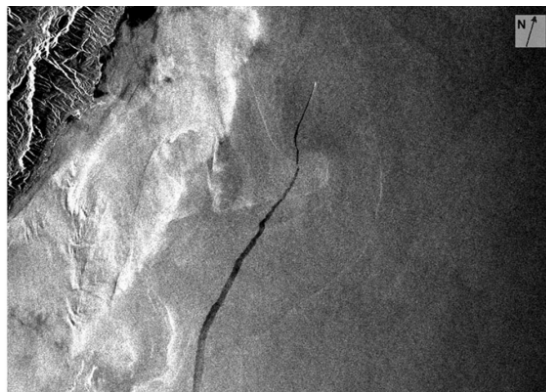
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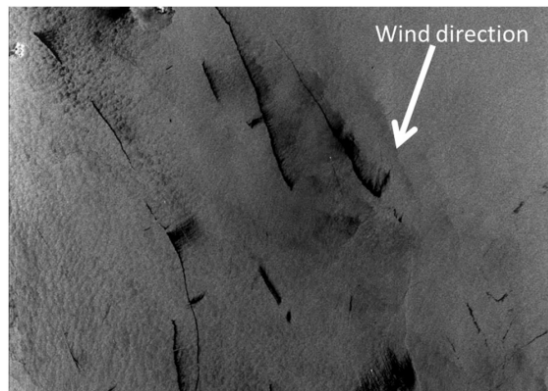
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Several polarimetric parameters have been derived from the scattering matrix, with the widely used parameters being the entropy (H), the anisotropy (A), and the mean scattering angle ( $\alpha$ ). A large number of papers have been published in the last decade dealing with SAR polarimetry for oil spill detection (for a review, see, e.g., Migliaccio et al., 2015) in which it is claimed that SAR polarimetry is also beneficial for discriminating between mineral oil films and biogenic slicks.



**Fig. 3.** SAR image acquired by the ERS-1 satellite on 20 May 1994 The oil disperses with time causing the oil trail to widen.



**Fig. 4.** SAR image acquired by the European Remote Sensing satellite ERS-2 The wind blew from a northeasterly direction causing the feathering oil trails.

Identifying oil films by the position/shape of the dark areas is the most viable method. It is possible, for example, 1) when a dark line is located behind a ship visible on a SAR image as a bright spot (Fig. 3), 2) when a linear dark feature broadens from one end to the other (Fig. 3) or 3) when the dark patch has a feathered shape (Fig. 4). The broadening of the linear feature is due to lateral diffusion which increases with time after spillage. The feathered shape is a consequence of the fact that the wind has a stronger grip on the heavier components of the oil film and thus these components are moved faster by the wind than the lighter components. Thus, the downwind side of mineral oil films usually have sharp boundaries. Biogenic slicks cannot have such feathered shapes because of their monomolecular structure. Oil originating from oil seeps (natural seepages from a hydrocarbon reserves) or oil platforms/oil terminals can often be detected by using time series of SAR images. The oil films manifest themselves as recurring features at the same location (Suresh et al., 2015). MacDonald et al. (2015) have used this approach to map the extensive natural seeps in the Gulf of Mexico.

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OIL SPILL DISCRIMINATION METHODS	DEPEND ON THE FEATURES	RESULT
reduction of the NRCS	1) the type of oil, 2)time after spillage (changes temperature and its composition), 3) distribution of the oil within the oil patch, 4) wind speed and direction.	reduction of the NRCS by mineral oil films are 5 to 12 dB, 9.3 dB by crude oil and of 8.3 dB by emulsion
differences in position and shape	1) when a dark line is located behind a ship visible on a SAR image as a bright spot 2) when a linear dark feature broadens from one end to the other 3)when the dark patch has a feathered shape	Biogenic slicks cannot have such feathered shapes because of their monomolecular structure but uncertainty always remains.
differences in texture	They break into patches.	cannot always be used as a reliable indicator for discriminating between mineral oil films and biogenic slick.
differences in the statistics of the image intensity	$I = \tau \cdot X$ , where $\tau$ describes the variation of the SAR image intensity due the physical processes (texture) and $X$ the variation due to speckle	statistics of the co-polarized phase difference performs better
using polarimetric parameters	to determine the scattering mechanisms causing observed radar signatures, like Bragg scattering and multiple scattering	challenging task and requires unique validation methods

**Table 1 Conventional methods to discriminate oil silks**

## IV. ALGORITHMS THAT MINIMIZES THE VARIATION DUE TO WIND AND WAVES.

The exact location of oil spills is essential and meaningful for simulating of the trajectory. The RGEDOM method presented in this paper is based on region growing and adaptive threshold segmentation. Experiments demonstrated that the RGEDOM method can work more effectively than comparator detectors for oil spill contexts. The SAR images are heterogeneous, although oil slicks are usually characterized by dark coloration, such coloration is not always synonymous with oil spill areas, instead, it could reflect the influence of the wind, wave and other factors. This method aimed to detect and approximate oil based on threshold segmentation and edge detection. Then, by using region growing to match the results of threshold segmentation from eight directions centers on the location of the oil texting by edge detection, which can produce results which are more accurate and reliable.

Nevertheless, there are further influencing factors which require investigation, particularly disruptive factors should be considered. Finally, in future, this newly developed method should be auto-adjusted to adapt to the different climate background of oil spills and the multiple manifestations of ocean noise.( Yang Zhao, 2017).

One of the principal limitations of SAR-based oil spill mapping is the issue of discriminating oil covered water from other dark ocean features such as low wind areas. To mitigate this limitation, an approach for oil spill detection from SAR images based on the multiscale time-frequency theory was pre- sented in this paper. The SLICK approach, which includes a combination of a normalization step, a data enhancement and filtering step, and the application of the multiscale oil spill CD technique, was adapted from Ajadi et al. to arrive at an optimized method for oil spill detection. A technique based on LR was presented first to normalize the reflectivity properties of ocean water and maximize the visibility of oil in water. The importance of LR is demonstrated using simulated dataset as well as through application

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to real datasets in Sections III and IV, respectively. The method of LR is robust, simple, and well suited to an unsupervised CD approach. Integration of modern nonlocal mean filtering and UDWT techniques provided robustness against SAR-inherent Speckle noise. In addition, our oil spill CD technique showed improved results when an EM algorithm with mathematical morphology was integrated into the workflow. The capability to preserve geometric details in the border regions of a spill were demonstrated when fusion at the decision level by an “optimal” scale selection was employed. To analyze the capabilities and limitations of the SLICK approach, we conducted a broad range of performance assessments. We used a SAR simulation concept to study the performance of our method in distinguishing true spills from low-wind look-alikes. To enable a sufficient assessment of the developed technology, we simulated data at two different frequencies, each composed of patches with two different surface wind speeds. Spill signatures of different sizes were included in the simulated patches. We extracted spill information from these data using our algorithm and compared the results to a state-of-the-art DSD concept. We also used the simulation concept to create spill signatures of various sizes and provided a range of statistical measures to analyze the effect of spill size on the performance. We conducted further performance analysis on real oil spill data. We showed the essential normalizing effect of the LR transform and demonstrated the benefits of multiscale processing for spill/water separation. We applied the SLICK approach to a wide range of spill situations including compact large-scale spills, slicks with complex outlines, as well as linear spills more typical for ship-based releases. For one of our real datasets, we conducted an extensive comparison of our algorithm to four different state-of-the-art reference algorithms. Analyzing the performance of our approach using both a simulated oil spill and a real oil spill event dataset, we found that our approach achieved high detection rates for all tested scenarios and compared favorably to reference techniques (Olaniyi A. Ajadi, 2018)

In the image analysis process, the most crucial task is the discrimination of oil spills and look-alike phenomena e.g., low wind area, wind front area and natural slicks on SAR. A support vector machine is employed to remote sensing image classification, which can obtain the oil spill area precisely considered with the weather conditions. The Dalian oil spill event simulation results demonstrate the validity of SVM for SAR image segmentation. (Jianchao Fan, 2015)

Oil spill detection using synthetic aperture radar (SAR) images plays a vital role in oil slick monitoring on the sea surface. In addition to oil spills, SAR images encounters a large number of similar phenomena called “lookalikes”. Choosing a method of discriminating between oil spills and lookalikes with high accuracy is a necessity. In this paper, a new algorithm is proposed for discrimination between oil spills and lookalikes, which consists of the following four main parts. 1) Dark spot detection in SAR images. 2) Shape-based feature extraction of oil spills and lookalikes elect from dark spots within the previous stage. 3) Feature transformation using the NMF algorithm. 4) Classification. To analyse the performance of the proposed algorithm, SAR images are used for testing. It provides promising results for both dark spot detection and oil spill classification. The average error rate of dark spot detection for a typical image was 1% and it may discriminate between oil spills and lookalikes with a medium accuracy of 96% using feature transformation modes after transforming the features and classifying them using the K-nearest neighbor classifier (Asma Raeisi., 2018).

## V. DISCUSSIONS AND CONCLUSION

Whereas, this survey paper depicts the different approaches in discriminating the oil spill from biogenic factors and their result. Among this discriminating approach other feature due to which the misclassification occurs is low wind areas. To eliminate this, LR is used which is robust, simple, and well suited to an unsupervised CD approach. From this survey, multi image analysis technique using LR performs well in oil spill discrimination even in low wind areas.

Future work can be focussed on discrimination using size and shape on different areas such as oceans, ice filled areas etc. It can also be done using gamma distribution in high wind areas.

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