

# DETECTION OF OIL SPILLS AND ANALYSIS OF ITS FEATURES USING SEGMENTATION

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## ABSTRACT

*This paper provides a comprehensive review of the use for detection of slicks features using kmeans algorithm. Oil spills are seriously affecting the marine ecosystem and cause political and scientific concern since they seriously effect fragile marine and coastal ecosystem. Pollutant discharges affect the quality of sea water. Satellite images can improve the possibilities for the detection of oil spills as they cover large areas and offer an economical and easier way of continuous coast areas patrolling. In order to detect oil spills SAR images have been used. This paper provides an overview of the methodologies used to detect oil spills on the radar images. Approaches to distinguish oil spills from other natural phenomena are performed here.*

**Keyword:-** Day-night band (DNB), feature extraction, Moderate Resolution Imaging Spectroradiometer (MODIS), moon glint, morphological operator, noise reduction, oil slicks, Visible Infrared Imager Radiometer Suite (VIIRS).

## 1. INTRODUCTION

Satellite images of reflected sunlight have been used to detect and monitor oil spills in oceans. However, such a capacity is often hindered by the image noise due to either a low signal-to-noise ratio or other image features such as clouds or cloud shadows. The problem is particularly severe for nighttime images captured by the Visible Infrared Imager Radiometer Suite (VIIRS). Oil spills can cause serious damage to marine and coastal ecosystems. Remote sensing techniques, with the development of state-of-the-art sensors and algorithms, serve as effective means to monitor and assess oil pollution in oceans and to guide coastal resource management. The Visible Infrared Imager Radiometer Suite (VIIRS) has similar orbital characteristics and a wider swath than MODIS and thus is also suitable for oil spill detection

under sun glint and cloud-free conditions. Indeed, VIIRS module is meant for capturing oil spills during night time under moon glint.

Oil Spills can cause serious damage to marine and coastal eco systems. Natural oil seeps account for a large percentage of crude oil entering the ecosystem; hence, ecological adaptations can occur at a geological time scale. Remote sensing techniques, with the development of state of- the-art sensors and algorithms, serve as effective means to monitor and assess oil pollution in oceans and to guide coastal resource management. Currently, most satellite observations of oil spills in oceans rely on synthetic aperture radar (SAR) data because of their high spatial resolution, transparency to most clouds, and day–night operability. optical sensors such as MODIS also have the capacity to detect oil spills under sun glint based on the similar wave-damping principles as used by SAR. The Visible Infrared Imager Radiometer Suite (VIIRS) has similar orbital characteristics and a wider swath than MODIS and thus is also suitable for oil spill detection under sun glint and cloud-free conditions. Indeed, VIIRS imagery collected at night may be also used to capture oil slick features under moon glint. A major obstacle in the routine application of oil slick feature extraction from optical remote sensing imagery is image noise and other natural features. This is particularly true for VIIRS nighttime imagery where image pixelization noise is apparent.

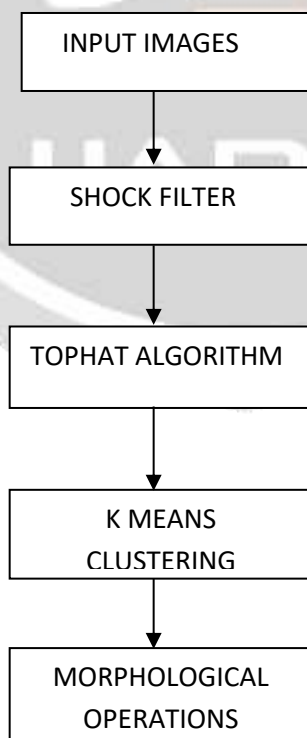
### 1.1 EXISTING SCHEME

Lee, Gamma, and Kuan filters can use large convolution templates to get satisfactory results, they also simultaneously blur the shape boundary and decrease the accuracy of feature extraction. Edge detection algorithms face a similar issue, where a small convolution window preserves noise, whereas a larger window blurs slick features.

### 1.2 PROPOSED SCHEME

Oil slick features often have relatively narrow widths particularly when they come from natural seeps, noise filtering should both preserve the narrow features and avoid breaking coherent line features. A Gaussian filtering window can be applied to achieve smoothing. Perform image enhancement also to identify the detected parts of the oil slick features.

. In proposed scheme, VIIRS nighttime images are taken, naturally it having white speckle noise. It can be removed by using Gaussian filter, it can remove noises only slick nature to be retrieved. Enhance the image by using histogram equalization. Apply threshold filtering to segment the oil slick features



**FIGURE 1:BLOCK DIAGRAM**

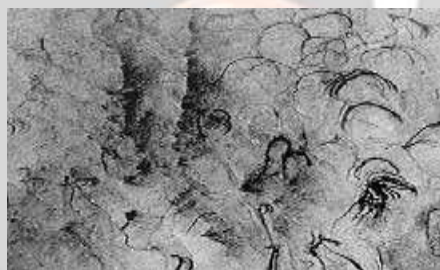
### 1.3 BLOCK DIAGRAM EXPLANATION

From the input image RGB is converted into gray scale image. Then it is converted into black and white image. Select the region to extract oil spill area and the noise is removed by using shock filter. Denoised image will be obtained. For increasing the contrast, use top-hat algorithm which gives us a top-hat image. Then thresholding process will take place. Hence we consider a threshold point and compare it with the image pixel value that gives the otsu output image. Morphological operation will take place to extract white pixels in the border. Hence it gives the value of oil spills.

### 1.4 INPUT IMAGES

Satellite images of reflected sunlight have been used to detect and monitor oil spills in oceans. However, such a capacity is often hindered by the image noise due to either a low signal-to-noise ratio or other image features such as clouds or cloud shadows. The problem is particularly severe for nighttime images captured by the Visible Infrared Imager Radiometer Suite (VIIRS). Oil spills can cause serious damage to marine and coastal ecosystems.

Remote sensing techniques, with the development of state-of-the-art sensors and algorithms, serve as effective means to monitor and assess oil pollution in oceans and to guide coastal resource management.



**FIGURE 2: GRAY SCALE INPUT IMAGE**

Remote sensing offers the advantage of being able to observe events in remote and often inaccessible areas. For example, oil spills from ruptured pipelines, may go unchecked for a period of time because of uncertainty of the exact location of the spill, and limited knowledge of the extent of the spill. Remote sensing can be used to both detect and monitor spills.

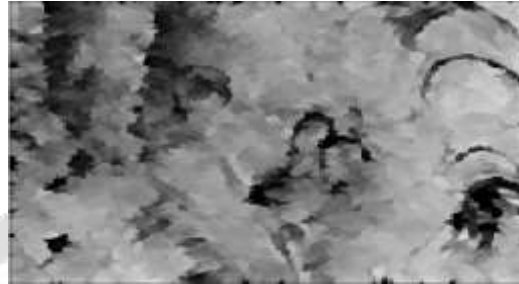
For ocean spills, remote sensing data can provide information on the rate and direction of oil movement through multi-temporal imaging, and input to drift prediction modelling and may facilitate in targeting clean-up and control efforts. Remote sensing devices used include the use of infrared video and photography from airborne platforms, thermal infrared imaging, airborne laser fluorosensors, airborne and space-borne optical sensors, as well as airborne and spaceborne SAR. SAR sensors have an advantage over optical sensors in that they can provide data under poor weather conditions and during darkness.

### 1.5 SHOCK FILTER

The presence of noise is a major problem which is mainly due to various processes dealing with document images (acquisition, transmission, storage ...). Whatever the level of noise is high enough; this could affect the usefulness of these images. In fact, such degradation limits enormously textual image processing, like image segmentation and binarization. Consequently, it is mandatory to introduce a pre-processing step to remove undesirable details inherent to noise with a correct trade-off between important features (corners, edges, boundaries) preservation and enhancement. For instance, the recourse for an enhancement process is required for a better visibility and dissimilarity between different image features and even to avoid the generation of blurred edges. The enhancement process is thus useful to overcome the limitation of the denoising process in some circumstances and even to improve its performances. The literature presents a variety of image denoising and enhancement algorithms where each has its drawbacks and advantages. The review of these algorithms is out of the scope of this paper. Our main concern is partial differential equation (PDE) based approaches. The latter is a general framework for the denoising/enhancement purpose, developed even in a coupled or independent manner. The use of PDE based non-linear diffusion techniques in the denoising task have been deserved a lot of attention since the early work of Perona

and Malik. These techniques compared to linear diffusion techniques are more attractive since they outperform them in preserving important image features while removing noise. Nevertheless, the smoothing property of these techniques could introduce a more or less blur that generates pressing needs for additional stronger sharpening qualities. As a solution some works in the continuity to the study of Alvarez et al propose to join in a common framework a non-linear diffusion process with a shock filter, the most well-known sharpening PDE..

Shock filters perform erosion and dilation. There's a shock discontinuity at the border.



**FIGURE 3: DENOISED OUTPUT IMAGE**

The resulting effect is basically enhancement/sharpening of the input image.

Two methods are used in shock filter are Gaussian and mask size. Gaussian is used as a filter in order to remove the noise. And then accuracy is low in edge detection technique in the existing system. In order to get accuracy we are using tophat algorithm in proposed system. In morphological operation image enhancement also to identify the detected parts of the oil slick features. Boundary calculation is very easy to calculate in the proposed system.

### 1.6 TOPHAT ALGORITHM

Tophat algorithm is meant for deblurring the captured images. The contrast level is increased. The black top-hat transform is defined dually as the difference between the closing and the input image.

Filtering is applied on binary image itself, morphological opening is computed and subtracted from the original image in order to obtain output same as that of input.

**FIGURE 4: TOPHAT IMAGE**





**FIGURE 5:EDGE DETECTION**

### 1.7 K MEANS CLUSTERING ALGORITHM

Here n observations are split into k clusters. For each centre k centre value is assigned & defined. K is the centre point of the cluster. For each k value, different output is obtained. K value is chosen in such a way that it should be far away from the pixel value.

$$J(V) = \sum_{i=1}^c \sum_{j=1}^{c_i} (\|x_i - v_j\|)^2 \quad (1)$$

' $c_i$ ' is the number of data points in  $i^{\text{th}}$  cluster.  
' $c$ ' is the number of cluster centers

### 1.8 MORPHOLOGICAL OPERATIONS

Morphological operation will take place to extract white pixels in the border. From the dilated image, morphological image is obtained. The output image is obtained by clearing the borders.

Then the affected oil slick area is displayed in message box.

In order to reduce noise, morphological operators are applied to gray level images. Morphological operators can also be applied to gray level images.

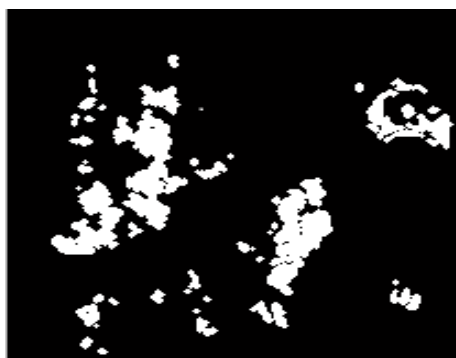
### 1.9 EXPERIMENTAL RESULTS

Based on these images it will be given to the morphological operator which can be extract the oil like features. Morphological operator is meant for removing the white pixels in the border. Threshold value is based on the AOI standard deviation and scaling factor. Based on the threshold value oil slick features are extracted.



**FIGURE 6:MORPHOLOGICAL IMAGE**

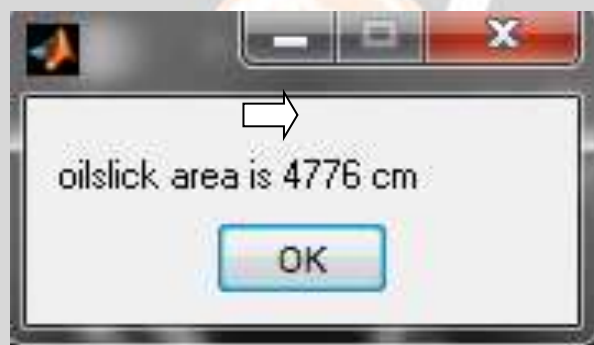




**FIGURE 7: OUTPUT IMAGE**

Morphological operation will take place to extract white pixels in the border From the dilated image, morphological image is obtained. The output image is obtained by clearing the borders.

From this output image the location of oil slick is found and the area was calculated in centimere and it is displayed in the message box output.



**FIGURE 8: AFFECTED OILSLICK AREA**

## 2.DISCUSSION AND CONCLUSION

A new feature extraction method has been developed to extract oil-like slick features from noisy VIIRS DNB imagery and MODIS imagery in a semiautomatic fashion. This is because the low SNR of the VIIRS DNB imagery and many other features in both the VIIRS and MODIS images make it extremely difficult to extract features automatically, and previously established methods for SAR image segmentation do not work well. The SNR of the VIIRS DNB imagery under moon glint used in this letter has been estimated to be 30:1–50:1 based on the method of Hu et al.. The feature extraction method is based on a series of processing steps including digital enhancement and morphologic operations in order to delineate slick features from the noisy background, which often contains other image features. The examples here show preliminary success in extracting oil slick features from the VIIRS DNB imagery. Further experiments indicate its general applicability to MODIS daytime imagery (645- and 859-nm bands) for their higher spatial resolution and higher SNRs. The method, however, requires human intervention to determine the optimal threshold values and thus cannot be fully automated at this stage. Under certain circumstances, the roundness parameters and the minimum pixel number both need to be adjusted in order to retain suspect features while removing noise. This is particularly true over large areas where there may be both positive and negative contrasting features within a single image. Future efforts therefore may be dedicated to

automatically determining parameters in the segmentation process, where a roaming window can be adopted to loop through the entire image with reduced human interaction. In any case, given the numerous slick features in noisy optical remote sensing images and the current manual delineation method such as those used during the Deepwater Horizon oil spill by both academia and operational agencies such as the U.S. National Oceanic and Atmospheric Administration, the proposed feature extraction method represents one step forward toward the long-term goal of fully automatic.

In the future, the proposed work will be fully automatic and extended by calculating the area ,accuracy,of the affected region for providing alerts to early warning systems (EWS) in environmental monitoring.

### 3.REFERENCES

- [1] A. Taravat and D. F. Frate, "Development of band ratioing algorithms and neural networks to detection of oil spills using Landsat ETM+ data," EURASIP J. Adv. Signal Process., vol. 107, pp. 1–8, Jan. 2012.
- [2] Oil in the Sea III: Inputs, Fates, and Effects, The National Academies Press, Washington, DC, USA, 2003.
- [3] M. F. Fingas and C. E. Brown, "Review of oil spill remote sensing," Spill Sci. Technol. Bull., vol. 4, no. 4, pp. 199–208, 1997.
- [4] C. Brekke and A. H. S. Solberg, "Oil spill detection by satellite remote sensing," Remote Sens. Environ., vol. 95, no. 1, pp. 1–13, Mar. 2005.
- [5] I. Leifer et al., "State of the art satellite and airborne marine oil spill remote sensing: Application to the BP Deepwater Horizon oil spill," Remote Sens. Environ., vol. 124, pp. 185–209, Sep. 2012.
- [6] G.-P. Oscar, I. MacDonald, C. Hu, J. Svejksky, and M. Hess, "Detection of floating oil anomalies from the Deepwater Horizon oil spill with synthetic aperture radar," Oceanography, vol. 26, no. 2, pp. 124–137, 2013.
- [7] C. Hu, X. Li, W. G. Pichel, and F. E. Muller-Karger, "Detection of natural oil slicks in the NW Gulf of Mexico using MODIS imagery," Geophys. Res. Lett., vol. 36, pp. 1–5, Jan. 2009.