DEVELOPMENT OF AN ALGORITHM FOR AUTOMATIC DETECTION OF OIL SLICKS FROM SYNTHETIC APERTURE RADAR (SAR) IMAGERY IN THE GULF OF GUINEA

[1]Amadi Afua Sefah-Twerefour, [2]George Wiafe and [3]Kwame Adu Agyekum

Department of Oceanography and Fisheries, University of Ghana, P.O. Box LG 99, Legon-Ghana.
[1]staamadi@gmail.com; [2]wiafeg@ug.edu.gh; [3]kaagyekum@gmail.com

ABSTRACT

Pollution in the marine environment caused by oil spills is of great concern to coastal states due to its ecological, environmental and socio-economic impacts. The main objective of this research was to develop an adaptive oil spill detection algorithm for the Gulf of Guinea, and to estimate the location and spatial extent of oil slick in an acquired SAR imagery. The relevance of the use of space borne data for oil slick monitoring is evident in increased vessel traffic and oil drilling activities off the coast of West Africa. Image processing of acquired SAR image of the region involved the application of a median filter, local thresholding, classification, area calculation, and location extraction. Two dark spots were classified as slicks on Radarsat-2 imagery acquired on 18 May, 2008. The information derived from this research is essential for automatic processing and future implementation of oil slick detection and monitoring programme in the Gulf of Guinea.

Index Terms**—** Oil pollution, Synthetic aperture radar, Radar detection

1. INTRODUCTION

Oil spills at sea are a phenomenon that has caused great worry to man and destroyed habitats ever since humans resorted to the use of fossil fuel as an energy source. This is due to the attendant environmental and socio economic problems caused by such spills. The risk of oil spills at sea does not only come from the oil rigs but also the transportation and discharge of oil by tankers [3]. It is estimated that 0.25% of the world's oil production ends up in the ocean [7].

Various means have been devised to properly monitor and manage oil spills. Synthetic Aperture Radar (SAR) is the ideal monitoring system to adopt in oil spill monitoring [8]. It can view a spill at a glance, penetrate cloud cover (no other sensor so far can image through cloud cover) [16] and give high image resolution [9]. However, it is unable to estimate the thickness of the spill and oil type [13; 4]. In SAR images, the physical mechanism that allows detection of oil spill is the dampening of capillary waves present on the ocean surface [19]. These capillary waves produce backscattering of the radar incident pulse due to a Bragg scattering mechanism [17]. As a result, ocean regions containing oil are dark in contrast with the background radar signal [El Zaart *et al*., 1998; Hovl *et al*., 1994; Solberg and Rune, 1996; cited in 10].

The research is aimed at developing adaptive oil spill detection algorithm using space-borne radar imageries from the Gulf of Guinea, and which could be used to estimate the location and spatial extent of the detected oil slick. Recent discovery of oil by some Gulf of Guinea states e.g. Equatorial Guinea and Ghana in addition to established oil producing countries such as Nigeria, poses environmental threats to living coastal and oceanic resources. Hence, there is an urgent need to develop monitoring capabilities to detect and provide information of the rate and direction of spread of oil.

2. METHODOLOGY

The SAR image was obtained from the Canadian Space Agency (CSA), dated 18th May, 2008 at 10:50:44 GMT, by the RADARSAT-2. The study used MATLAB Version 7.6.0.324 (Matrix Laboratory by MathWorks Inc, 2008) image processing software to process the SAR image. Image processing of acquired SAR image of the region involved filtering, thresholding, classification, computing of spill area and spill location extraction (Figure 1). A median filter was applied to the entire image to reduce speckles. Local thresholding method was used in creating the binary image to make thresholding adaptive using mean and standard deviation statistics of a window size of 500x500. This ensures that even for an image with a non-uniform contrast a good approximation of statistics for sections of the image would provide an appropriate value to segment the image.

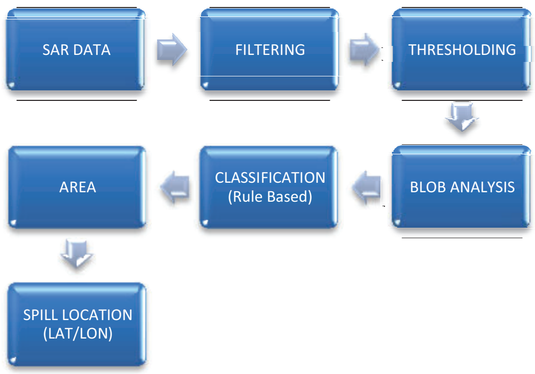

Figure 1 Oil spill detection and classification method

The classification rule was generated first from the area of coverage based on blobs with pixel area coverage more than or equal to 100 pixels. Blobs with more than 5000 pixels were classified as potential oil slicks. These blobs were chosen to go through the entropy classification stage. The entropy of the background was analysed as well as that of the selected dark region (i.e. verified slick) to arrive at an entropy range for the dark spots to be classified as slicks. The texture of the blobs were analysed using an entropy range of 1.5 to 1.8 after analyzing the background entropy. The entropy here is a statistical measure of randomness (absolute variability in backscatter change over selected image sections) [15]. The entropy was based on the algorithm:

$$-\mathbf{Sum}(p.*\log_2(p)) \qquad \text{(Equation 1)}$$

where p is the histogram counts generated from the histogram.

The areas of the classified slicks were calculated using the nominal spatial resolution of the satellite imagery. The centroids of the two spills were plotted on the original image then their locations, in terms of latitudes and longitudes, extracted. This was done by calculating geographic coordinates from a geometric model using tie-points and image coordinates.

3. RESULTS

The detection algorithm developed compared the mean of all pixel values within the 500x500 local window moving through the image, to all the pixel values in the filtered image. The detection algorithm developed was:

$$\mathbf{c(i,j) > \mu_c * Facta} \qquad \text{(Equation 2)}$$

Where Facta = σ_{image} / $\mu_{image;}$ c = moving window; σ_{image} = standard deviation of image; μ_{image} = mean of image; μ_c = mean of moving window.

The median filter applied before the segmentation removed speckle from the image and hence provided a clear contrast between the original and the filtered image (Figure 2).

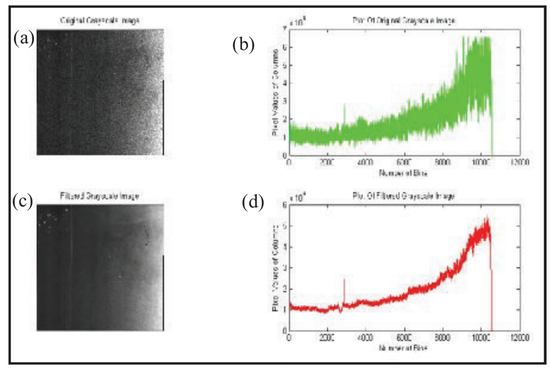

Figure 2 The filtered and original images with their respective plots

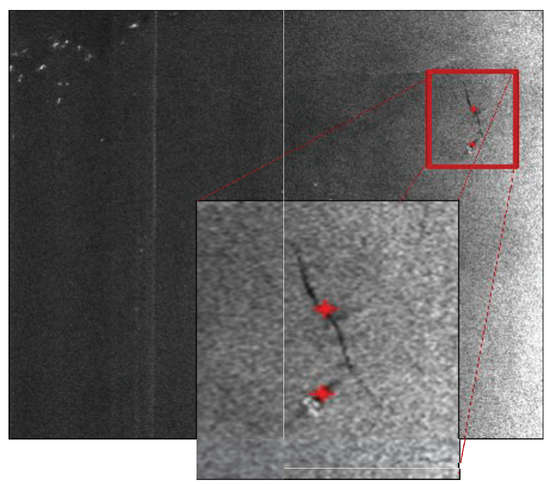

Figure 3 The two classified slicks with centres indicated by red dots

Two dark spots were classified as slicks (Figure 3) and their areas as well as their locations determined (Table 1).

Table 1 Classified slicks with respective locations and area of coverage

		Location	
Slick	Area	Latitude	Longitude
1(longer)	31, 700, 700 m² (31, 700.7 km²)	3°26'51"S	2°03'02"E
2	11, 729, 700 m² (11, 729.7 km²)	3°30'08"S	2°23'34"E

4. DISCUSSION

The detection algorithm, termed, the *Mean-Standard deviation Algorithm*, used a standard deviation-mean technique to make the algorithm an adaptive one. The ratio of the standard deviation and the mean of the entire image were employed in making the algorithm adaptive at the segmentation stage.

Instead of the application of a mean filter [6; 5], an opening and closing filtering [1], or a Sobel operator [12], for noise reduction, this study used a median filter. The median filter allowed the slicks to appear distinctly in the filtered image since it enhanced pixel distribution. A motion filter failed to make the threshold adaptive enough.

Local thresholding was best due to the uneven brightness of the SAR imagery. [2] were the first to attempt such a method of segmentation. The algorithm detected bimodal histograms in an NxN window and N was set to 25 pixels. In this study, N was set to *500* pixels. To ensure high dark spot detection ability, the adaptive algorithm developed in this study was modified to make use of the local mean and the mean and standard deviation statistics of the image.

A similar but slightly different approach to the segmentation employed in this study was used by [6;5] where the threshold value was set at a value lower than the estimated mean within the window. In [18], the size of the image window used varied with the brightness and contrast values of large areas in the image. This study, however, used a local thresholding method, setting the threshold value lower than the pixel values within the moving window. The ratio of the standard deviation and mean of the entire image (i.e. Facta) gave a value that made the algorithm adaptive.

The three geometric features extracted from the dark spots in this work were not used in slick classification for lack of a good concrete basis to reject or accept any. [14] asserted that extraction of good features is important nevertheless if there was no guideline as to the mode of acquisition then this poses a problem. In the case of spot contextual features, the location of the slick relative to the shore, oil rig or ship is evaluated. Most of the dark spots detected in this study were in very close proximity to ships and this is buttressed by the fact that the image was from a shipping route and also close to shore. Using contextual analysis, [11] described a supervised discrimination algorithm.

In this study, area of coverage and entropy were used as classifiers. Area coverage (pixel coverage) >=100 were first considered which reduced the dark spots to 6% of the initial total. Given the use of a single image, area coverage >5000 was chosen to reduce error introduction into the classifier but small slick detection capability of the algorithm is an advantage especially in the monitoring of illegal oil discharges at sea.

The entropy, used as the second classifier, was derived from examining the entropies of the known slick, the entire image and the background. The entropy is most likely a better property to use as a classifier due its non-dependence on slick shape and the fact that oil is amorphous. The entropy here is a statistical measure of randomness (absolute variability in backscatter change over selected image sections) [15]. The estimated range of the entropy used as a classifier was from 1.5 to 1.8.

5. CONCLUSION

The information derived from this research, using the algorithms developed, is key for automatic processing and future implementation of slick detection and monitoring programme within the Gulf of Guinea. This will enable agencies responsible for intervention to devise appropriate management and control plans and speed up their response time aiding in the protection of living marine resources. Further testing of the entropy range would help improve the algorithm.

6. ACKNOWLEDGEMENT

We acknowledge the Canadian Space Agency (CSA) for providing the imagery used in this research work.

7. REFERENCES

[1] A. Gasull, X. Fabregas, J. Jimenez, F. Marques, V. Moreno, and M. Herrero. Oil spills detection in SAR images using mathematical morphology. *Proc. EUSIPCO'2002, Toulouse, France,* vol. 1, pp. 25–28, 2002.

[2] A. Skøbelv, and Wahl, T. Oil spill detection using satellite based SAR, Phase 1B competition report. Tech. rep., Norwegian Defence Research Establishment, 1993.

[3] A.H. Espedal, and O.M. Johannessen. Detection of oil spills near offshore installations using synthetic aperture radar (SAR). *International Journal of Remote Sensing,* vol. 21**,** No**.** 11, pp**.** 2141-2144. 2000.

[4] A.H.S Solberg, C. Brekke, and P.O. Usøy. Oil Spill Detection in RADARSAT and ENVISAT SAR Images. *IEEE Transactions on Geoscience and Remote Sensing*, vol. 45, no. 3, pp. 746-752, March 2007.

[5] A.H.S. Solberg, S. T. Dokken, and R. Solberg. Automatic detection of oil spills in ENVISAT, RADARSAT and ERS SAR images. *Proc. IGARSS'03,* vol. 4, pp. 2747–2749, 2003.

[6] A.H.S. Solberg, G. Storvik, R. Solberg, and E. Volden. Automatic detection of oil spills in ERS SAR images. *IEEE Transactions on Geoscience and Remote Sensing*, July, vol. 37, no. 4, pp. 1916-1924, July 1999.

[7] Alpers, W and Espedal, H.A. Oil and surfactants. In: Jackson, C.R and Apel, J.R., (Eds.). *SAR marine user's manual*. Chapter 11. Washington DC, National Oceanic and Atmospheric Administration, pp. 263-265, 2004.

[8] C. Brekke, and A.H.S. Solberg. Oil Spill Detection by Satellite Remote Sensing. *ELSEVIER, Remote Sensing of Environment* 95, pp. 1-13, (2005).

[9] F. Girard-Ardhuin, G. Mercier, F. Collard, and G. Garello. Operational oil slick characterization by SAR imagery and synergistic data. *IEEE J. Ocean.Engineering .July*, vol. 30, no.3, pp. 487–495. July 2005.

[10] H. Assilzadeh, and Y. Gao. Oil spill emergency response mapping for coastal mapping coastal areas using SAR imagery and GIS. *IEEE Geoscience and Remote Sensing*, pp. 1-3, January 2008.

[11] H. Espedal. Detection of oil spill and natural film in the marine environment by spaceborne SAR. Proc. IGARSS'99, vol. 3, pp. 1478– 1480, 1999.

[12] M. Barni, M. Betti, and A. Mecocci. A fuzzy approach to oil spill detection on SAR images. *Proc. IGARSS '95,* vol. Π, pp. 157– 159, 1995.

[13] M. Fingas, and C. Brown. Remote sensing of oil spill. *Sea Technology,* vol. 38**,** pp. 37-46, 1997.

[14] M. Kubat, R.C. Holte, and S. Matwin. Machine learning for the detection of oil spills in satellite radar images. *Machine Learning,* vol. 30, pp. 195–215, 1998.

[15] M. Marghany, and M. Hashim. Comparison between Radarsat-1sar Different Data Modes for Oil Spill Detection by Texture Algroithms. *Map Asia 2010 & ISG 2010, Kuala-Lumpur, Malaysia,* 26-28 July 2010.

[16] McCandless, S.W. Jr., and Jackson, C.R. Principles of synthetic aperture radar. In: Jackson, C.R and Apel, J.R., (Eds.) *SAR Marine User's Manual*. Washington DC: National Oceanic and Atmospheric Administration. pp. 1-2. 2004.

[17] P. Trivero, B. Fiscella, F. Gomez, and P. Pavese. SAR detection and characterization of sea surface slicks. *International Journal of Remote Sensing*, vol. 19, pp. 543–548, 1998.

[18] V. Karathanassi, K. Topouzelis, P. Pavlakis, D. Rokos. An object-oriented methodology to detect oil spills. *International Journal Remote Sensing*, vol. 27, pp. 5235-5251, 2006.

[19] Y. Arvelyna, M. Oshima, A. Kristijono, and I. Gunawan. Auto segmentation of oil slick in RADARSAT SAR image data around Rupat Island, Malacca Strait. *22nd Asian Conference on Remote Sensing,* pp.5-9, November 2001.