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A Study on Dark Spot Extraction Methods in Oil Spill SAR Imagery

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Abstract: The Accidental or intentional release of oil in the environment is known as oil spill. Among the different types of marine pollution, oil is a major menace to the sea. Oil on the water surface reduces the back scatter values which results in dark spot in SAR imagery. Different phenomena like low wind area, organic film, natural film, rain cells and others resulted in dark spot in SAR imagery. An important step in any oil spill detection system is the segmentation of dark areas in SAR images. Main issue in oil spill detection system is discrimination between oil spill and lookalikes. In order to discriminate oil spills from lookalikes the dark spots in the SAR imagery needs to be extracted. Different techniques are implemented by different methods mostly based on pixel values. In this paper, numbers of dark spot extraction methods are discussed to augment the oil spill detection system.

Keywords: *Oil spill, SAR imagery, lookalikes, dark spots, marine pollution*

1. Introduction

The major threat in the marine ecosystem is oil spills. The main cause of marine oil pollution is due to oil tanker accidents, ship traffic, close to oil platforms or in coastal of rivers. Remote sensing is used in the oil spill monitoring system. As the SAR images are not affected by cloud, day and night capturing facility, they are used for monitoring marine environment.

They include worldwide regular coverage, day-night imaging capability, independence of cloud coverage and ability to detect both oil spills and ships. The extracted information from the SAR images is highly dependent on the weather conditions. For example, the location of the oil spill, the shape of oil spill, and the contrast between the variation between the oil spills and the surroundings sea are all dependent on the weather conditions. Thus, a simple spot detection is not an object by itself. Higher-level analysis based on special characteristics for oil slicks is urgently needed and showed satisfying results. However, they present some drawbacks which make difficult to develop a fully automatic oil spills detection system.

Marine oil pollution dampens capillary waves polluted area will appear as a dark area in the SAR. The SAR images are processed to detect and segment dark spots. The oil spills are mainly characterized by their dark level with respect to the background. This feature suggests the use of a threshold based segmentation approach.

This paper is organized as follows: Section 2 elaborates the oil spill detection system. Section III discusses the different existing algorithms for dark spot extraction with their comparisons. Section IV discusses the experimental setup and results Section V presents the concluding and future work remarks.

2. The oil spill detection system

Detecting oil spill using SAR images is done in two steps: extraction and classification. Here the focus is on the extraction part, evaluating the possibilities offered by segmentation algorithms to detect dark spots in SAR images.

The enhanced and preprocessed SAR image is given as input to the dark spot extraction. Dark spot extraction (segmentation of dark spot) is considered as the main step in oil spill detection systems because clear dark spot extraction leads to proper identification of features. Several techniques have been presented in the literature for detecting dark formations in SAR images.

Image segmentation consists of partitioning an image into homogeneous regions that share some common proprieties. There are two main approaches in image segmentation: edge-based and region-based. Edge-based segmentation is based on discontinuities in the intensity of an image. Region-based segmentation is based on uniformity within a sub-region, using a desired property for example, intensity, color and texture. Automatic interpretation of images is a very difficult problem in computer vision. Several methods are developed in the last decade to improve the segmentation performance in computer vision for oil spill detection system. Table 1 shows the significant dark spot extraction algorithms available in the literature.

3. State of the Art

Rune Solberg et al [1] have developed an algorithm for detection of dark spots based on adaptive thresholding. The thresholding is based on an estimate of the typical backscatter level in a large window. The window is moved across the image in small steps to threshold all pixels in the scene.

An object oriented methodology for the image segmentation technique is introduced by Topouzelis et al in [2] for extracting the dark formations. A two stage threshold algorithm for dark area detection has been implemented. Segmentation takes the advantage of the different contrast and intensity values in Advanced Synthetic Aperture Radar (ASAR) image. The method detects dark areas with various brightness values located in different sea-state environments.

I.Keramitsogloua et al [3] extracted the dark area using the segmentation algorithm based on grey level thresholding. This algorithm splits the image into two classes: one having pixels below a user defined value and one above. This is an important operation for image dark region extraction. It is applied to each individual image pixel or group of pixels at a local or global level. A fuzzy based classifier is applied to classify the pixels. Sonia Pelizzaria et al [4] used Bayesian supervised and unsupervised segmentation algorithms for the segmentation of SAR images. The data term is modeled by a finite mixture of Gamma densities with a given predefined number of components. To estimate the parameters of the class conditional densities, a new expectation maximization algorithm is developed. It applies a multi-level logistic Markov random field enforcing local continuity in a statistical sense. The smoothness parameter controlling the degree of homogeneity imposed on the scene is automatically estimated. The classical coding and least square fit methods are also considered. The Maximum Posteriori (MAP) segmentation is computed efficiently by means of recent graph-cut techniques. The Expansion algorithm extends the methodology to an optional number of classes. This approach has been tested on ERS and ENVISAT scenes containing oil spills.

An edge detection filter is applied on the despeckled image to extract the dark area in [5] by Gasull et al. Sobelg et al used adaptive thresholding algorithm for detecting dark spots in [6] [7]. The thresholding is based on an estimate of the typical backscatter level in a large window. The adaptive threshold is set to kdB below the estimated local mean backscatter level. Wind data is used to determine ‘k’ value.

Kanna et al [8] proposed an oil slick detection method based on hysteresis thresholding. This method is based on directional behavior of oil slick in the sea surface. Therefore directional hysteresis thresholding responses are first computed in order to highlight the dark spots, and to increase pixel connectivity in each Freeman direction. Those responses are then merged with the help of a Context Independent Constant Behaviour (CICB) operator to detect the dark slicks. This method has been tested on ERS SAR amplitude images of Mediterranean and Atlantic seas.

A.H.S.Solberg et al [6] presented a framework for automatic detection of oil spills in SAR images. Multi incident angle and multi polarization SAR data are used in this framework. Dark spots in the images are primarily detected by adaptive thresholding. For each of them a number of features are computed in order to classify the slick as either an oil slick or a `lookalike'. A classification scheme is utilized based on statistical modeling. A data set of about 100 images from each of the sensors ERS and RADARSAT are used.

Yessy et al [9] used Bayesian Map for speckle reduction and segmentation. In order to detect the coastal line, canny filter is used and Maximum Entropy method is used to extract the oil spill features.

S.B.Mansor et al [10] used SAR data for detecting oil spills to support the contingency plan at a specific location in Straits of Malacca. Several image processing methods such as Gamma distribution analysis, texture analysis, image composite analysis and image classification are applied. The preprocessed image is used to detect oil spill and its characteristics. This work focused on automatic dark slick detection and classification as early warning system for oil spill contingency planning. The framework developed by Solberg et al [11, 12] consists of three main parts namely, dark spot detection, spot feature extraction and spot classification. Detection of dark spots is done by adaptive thresholding (multiple approach using pyramids). For each detected spot, a number of features are computed in order to classify the slick as either an oil slick or a look-alike. A supervised classification scheme is then utilized based on combining statistical methods with a rule-based approach.

Fanny et al in [13] presented a qualitative comparison of four detection algorithms. In the first method, a succession of median and Sobel filters followed by a morphological mathematics combination of dilation and erosion are used. The second method is also a simple algorithm using smoothing followed by thresholding and Sobel filter. Third algorithm is a combination of gradient and attenuation relative to background level followed by morphological filters. The last method is a complex algorithm based on multi-scale analysis of the observed data because oil and sea spectra have different distribution signatures. All the segmentation methods give good results with simple images, but for complex and ambiguous areas other methods are needed.

***Table 1** Different Dark Spot Extraction algorithms*

Author	Dark Spot Extraction Method Used
Solberg et al	Adaptive thresholding
Fiscella et al	Land Masking and Selection of dark area based on average NRSC
A. Gasull et al	Edge detecting nonlinear filter-top hat filter
Sonia Pelizzaria et al	Bayesian supervised and unsupervised segmentation algorithms
Kanna et al	Hysteresis thresholding
Mansor et al	Texture analysis method
Francesco et al	Constant False Alarm Rate Algorithms
Kanaa et al	Modified morphological met pyramid based adaptive thresholding
Y.Zheng et al	Fuzzy clustering method
I.Keramitsogloua et al	Gray level thresholding
Montali et al	Thresholding based on multiscale pyramid approach.
Topouzelis et al	Object Oriented Methodology which uses intensity and contrast
Stephane et al	Hidden Marko Chain algorithm
K.Karantzalos et al	Geometric level set method
A. Akkartal	Thresholding Using GLCM homogeneity
Del Frate et al	Thresholding method
Hang le et al	Adaptive thresholding
M. Airouche et al	Active contour with PDE based Level set method
M.Cococcioni et al	ROI method
Maged Marghany	Lee algorithm & Entropy Texture algorithm and Fractal method
A.F. Sheta et al	Local and global thresholding techniques

K.Karantzalos et al in [16] used the geometric level set method which includes the curve evolution algorithm proposed by Chen Vase and Tsai et al. The method segments oil spills of different shapes.

Airouche et al in [17] have proposed an image segmentation method which uses the framework of active contours, as active contours always provide continuous boundaries of sub-regions.

They can also produce more reasonable segmentation results than traditional segmentation methods, and consequently improve the final results of image analysis. The mathematical implementation of the proposed active contour models is accomplished using level set method. By presenting contours as a level of a topological function, multiple contours are merged into one contour. A contour can be split into multiple contours and provide a good flexibility in the use of active contours.

A partial differential equation based level set method which represents the spill surface as an implicit propagation interface is used. Starting from an initial estimation with priori information, the level set method creates a set of speed functions to detect the position of the propagation interface. Specifically, the image intensity gradient and the curvature are utilized together to determine the speed and direction of propagation. This allows the front interface to propagate naturally with topological changes.

Significant protrusions and narrow regions give rise to stable and smooth boundaries that discriminate oil spills from the surrounding water. Their method has been tested to detect oil spills in real images. The advantages over the traditional image segmentation approaches have also been demonstrated.

The geometric level set method includes the curve evolution algorithm and energy functional proposed by Chen Vase and Tsai et al. This method employed to segment the oil spills of different shapes by K.Karantzalos et al [16]. The last step in the scheme is classification of oil spills and look-alikes. Geometric, statistical, shape and textural properties are extracted and are given as inputs to minimum distance classifier. Huang et al [18] used level set method for dark spot extraction.

After preprocessing the image, the neighboring pixels are compared and merged into regions if they are similar for segmentation. The method is used by Akkartal et al [19]. The algorithm runs iteratively to merge the resulting regions. Two neighboring regions, R_i and R_j, are merged based on thresholding condition and neighborhood condition. After segmentation, texture analysis is carried out using Gray Level Co-occurrence Matrix (GLCM) to analyse the textural properties. A. F. Sheta et al [20] used local and global thresholding techniques developed by Araujo et al in [21] and Chang et al in [22] to detect the dark spots. In [23] Y. Zheng et al used fuzzy clustering method for segmentation. Roslinah Samad et al in [24] masked the sea area from land area using histogram thresholding method. Edge detection filters are used to segment the dark area. Texture, shape and brightness analysis are also done. Finally an unsupervised classifier is used.

Derrode et al [15] used an enhanced vector Hidden Markov Chain (HMC) model. An unsupervised method for the segmentation of oil spills based on a multiscale decomposition and a Markovian model have been presented. The segmentation method utilizes the different states of the sea surface through its wave spectrum. The multiscale decomposition is implemented with a wavelet transform which acts as a multiscale differential operator. The estimation of the multidimensional pdf arising in the algorithm has been achieved by Principal Component Analysis. In PCA each component comes from the Pearson system of distributions (for the low-pass coefficients) or from the family of generalized Gaussians (for the high-pass coefficients). The segmentation strategy used detects different phenomena that have an impact on the sea surface wave spectrum and seems to be appropriate for the detection of oil spills on the sea surface. However, the stationary assumption of the Markov chain is a limitation for the analysis of full size radar images in an operational context. The lack of validity of this assumption induces a wrong segmentation where the oceanographic phenomena are mixed together in order to yield a Markov chain where parameters are stationary.

Pelizzari in [25] extends and generalizes a previously proposed Bayesian semi-supervised segmentation algorithm [26] for oil spill detection using SAR images. The methodology proposed in [4] assumes two classes and known smoothness parameter. The smoothness parameter controlling the degree of homogeneity imposed on the scene is automatically estimated and the number of used classes is optional. To extend the algorithm to an optional number of classes, the α-expansion algorithm is implemented. This algorithm is a graph-cut based technique that finds efficiently (polynomial complexity) the local minimum of the energy, (i.e, a labeling) within a known factor of the global minimum. To estimate the smoothness parameter of the MLL prior, two different techniques are tested, namely the Least Squares (LS) Fit and the Coding Method (CD). Semi-automatic estimation of the class parameters is also implemented. This is an improvement over the base algorithm [24], where parameter estimation is performed on a supervised way by requesting user defined regions of interest representing the water and the oil. The effectiveness of the approach is illustrated with simulated SAR images and real ERS and ENVISAT images.

4. Experimental results plenary talk

Dark spots are extracted using segmentation algorithms. Few algorithms like Adaptive thresholding, Fuzzy C-Means thresholding, Spatial Fuzzy C-Means with level set and Global Minimization of Active Contour model are the segmentation algorithms implemented to extract the Dark spots from SAR imagery.

The results of four algorithms are discussed in order to continue further processing. First, an oil Spill [26] SAR image of 256 X 256 containing dark spot is taken as input. Algorithms with default parameter values were applied on SAR images. Subjective method of evaluation is done here. The figure 1 shows the output image of the implemented algorithms. The objective method of evaluation is done by calculating Jaccard coefficient (JC) and Dice Similarity (DS).

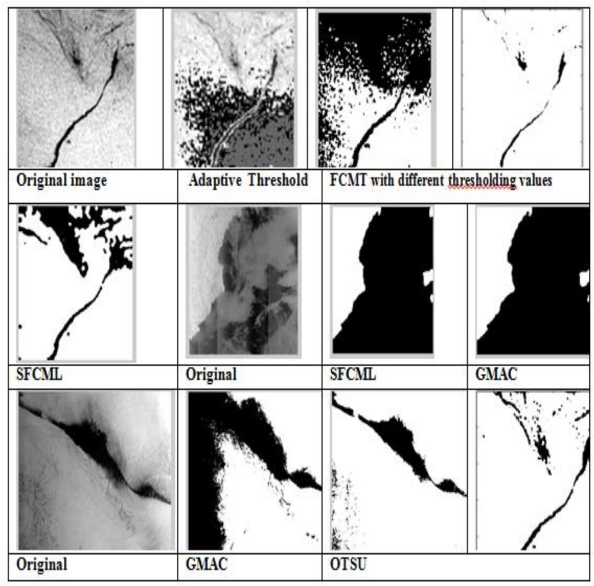

Figure 1 *Different Dark Spot Extraction Algorithms*

4.1. Jaccard Coefficient (JC)

Jaccard coefficient is defined as the ratio of the intersection of segmented area X and ground truth area Y to the union of segmented area X and ground truth area Y.

$$\mathrm{JC}(X,Y) = \frac{|X \cap Y|}{|X \cup Y|} \qquad (1)$$

JC is a normalized measure of the relative overlap in [0, 1]. A JC close to 1 indicates better segmentation.

4.2. Dice Similarity (DS)

Dice similarity (DS) measure computes the ratio of the intersection area divided by the mean sum of each individual area. Let x denote the segmented area and Y denote the ground truth area. Then the Dice similarity measure DS is defined as

$$\mathrm{DS}(X,Y) = \frac{2|X \cap Y|}{|X+Y|} \qquad (2)$$

When the DS is high, then the segmentation is said to be superior. The value ranges between 0 to 1. Therefore DS is expected to be high for better segmentation. The table 2 shows the similarity coefficient values by different segmentation methods. For calculating similarity coefficients the ground truth images are taken by manual method. One more ground truth image is taken from Otsu's method. The mean value of manual method and Otsu's method is taken to calculate similarity coefficients.

Table 2 *Similarity coefficients of Various Segmentation Algorithms*

ALGORITHMS	DC	RE
FCMT	0.805474	0.656984
GMAC	0.6058	0.4346
AT	0.723331	0.593623
SFCM	0.7596	0.6124
SFCM+L	0.5442	0.6924

The output image shows different algorithms are suitable for different image shapes. Some algorithms results in under segmentation where as some results in over segmentation. This study is done in order to overcome this difficulty and to devise an algorithm which can handle these problems.

5. Conclusion

Different dark spot extraction methods are discussed. The dark spots are extracted mainly using thresholding technique. Adaptive thresholding algorithm is mainly used to extract the dark spot based on the mean back scatter value by many authors. Hysteresis thresholding, Gaussion Log method, Bayesian method, mathematical morphology method and level set methods are some of the methods used in the literature. Main drawback with the thresholding methods is over segmentation as it depends on pixel values. Edge detection methods result in more number of segments and blobs in the extracted image. Initializing and re-initializing the energy of active contour method is time consuming. Hence, there is a need to develop a new technique to detect all the dark spots which eliminates the above drawbacks.

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