



## OILSPILL AND LOOK-ALIKE SPOTS FROM SAR IMAGERY USING OTSU METHOD AND ARTIFICIAL NEURAL NETWORK

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### Abstract:

*Oil spill pollution plays a significant role in damaging marine ecosystem. Discharge of oil due to tanker accidents has the most dangerous effects on marine environment. The main waste source is the ship based operational discharges. Synthetic Aperture Radar (SAR) can be effectively used for the detection and classification of oil spills. Oil spills appear as dark spots in SAR images. One major advantage of SAR is that it can generate imagery under all weather conditions. However, similar dark spots may arise from a range of unrelated meteorological and oceanographic phenomena, resulting in misidentification. A major focus of research in this area is the development of algorithms to distinguish 'oil spills' from 'look-alikes'. The features of detected dark spot are then extracted and classified to discriminate oil spills from look-alikes. This paper describes the development of a new approach to SAR oil spill detection using Segmentation method and Artificial Neural Networks (ANN). A SAR-based oil-spill detection process consists of three stages: image segmentation, feature extraction and object recognition (classification) of the segmented objects as oil spills or look-alikes. The image segmentation was performed with Otsu method. Classification has been done using Back Propagation Network and this network classifies objects into oil spills or look-alikes according to their feature parameters. Improved results have been achieved for the discrimination of oil spills and look-alikes.*

**Keywords:** SAR; Artificial Neural Network (ANN); Segmentation; Look-Alikes; Oil Spills.

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### 1. Introduction

A. Akkartal, et. al [1] had discussed about the Synthetic Aperture Radar (SAR) satellites as the main data sources to detect the oil spills discharged into the sea with sufficient accuracies. In this study, the advantages and disadvantages of using different radar images for oil spill detection in Marmara Sea were investigated. Akram A. Moustafaet. al [2] was proposed an artificial neural network training algorithm which is implemented in MATLAB language. This implementation is focused on the network parameters in order to get the optimal architecture of the network that means (the optimal neural network is the network that can reach the goals in minimum number

of training iterations and minimum time of training). The optimal solution was reached by minimum training time and minimum number of training iterations.

AlaaSheta, et. al [3] was proposed an method that consists of four main stages, namely: 1) Image enhancement; 2) Image segmentation 3) feature extraction; and 4) Object recognition of the segmented objects as oil spills or look-likes. The algorithm was trained on a large number of Synthetic Aperture Radar (SAR) images. The proposed thresholding algorithm can be considered an alternative to manual inspection for large ocean areas.

Promising results and high detection rates for the oil spills had been achieved. Anne H. Schistad Solberg, et. al [4] had presented algorithms for the automatic detection of oil spills in SAR images. The developed framework consists of first detecting dark spots in the image, then computing a set of features for each dark spot, before the spot is classified as either an oil slick or a “lookalike” (other oceanographic phenomena which resemble oil slicks). The classification rule is constructed by combining statistical modeling with a rule-based approach.

Camilla Brekke, et. al [5] presented the state of the art for oil spill detection in the world oceans. They discussed different satellite sensors and oil spill detectability under varying conditions. In particular, they concentrated on the use of manual and automatic approaches to discriminate between oil slicks and look-alikes based on pattern recognition. They concluded with a discussion of suggestions for further research with respect to oil spill detection systems. F. Nirchio, et. al [7] was proposed a probabilistic method was developed that distinguishes oil spills from other similar sea surface features in Synthetic Aperture Radar (SAR) images. It considers both the radiometric and the geometric characteristics of the areas under test. In order to minimize the operator intervention, it adopts automatic selection criteria to extract the potentially polluted areas from the images. Konstantinos N. Topouzeli [8], provided a comprehensive review of the use of Synthetic Aperture Radar images (SAR) for detection of illegal discharges from ships. It summarizes the current state of the art, covering operational and research aspects of the application.

Konstantinoskarantzalos, et. al [9] was proposed the level set based image segmentation was evaluated for the real-time detection and tracking of oil spills from SAR imagery. The developed processing scheme consists of a pre-processing step, in which an advanced image simplification, followed by a geometric level set segmentation for the detection for the detection of the possible oil spills. Finally a classification was performed for the separation of look-alikes leading to oil spill extraction. Krishna Kant Singh, et. al [10] was proposed importance of image segmentation and number of algorithms had been proposed to get the best results. In this paper the author had given a study of the various algorithms that are available for color image, text and gray scale image.

K. Topouzelis, et. al [11] was proposed the study as presentation, analysis and evaluation of the features in order to produce general rules adequate to identify oil spills in any SAR image. SAR image processing is based on a new multi-segmentation technique. As a first step, image objects in different scales were extracted using the multi-segmentation procedure. Following segmentation, a hierarchical network of image objects was developed, which simultaneously presents object information and fuzzy rules for classification. In experiments implemented in

SAR images, the method developed had successfully detected oil spills and look-alikes. Mahinda P. Pathegama, et. al [12] was proposed an algorithm to extract edge-end pixels together with their directional sensitivities as an augmentation to the currently available mathematical models. Radhika Viswanathan, et. al [13] was proposed about the different feature extraction and classification method for oil spill detection and their preliminary results.

In the present work, a new approach was developed and tested to distinguish oil spills from other similar oceanic features in marine SAR images. The discrimination between oil spills and look-alikes is usually done with the use of a classification procedure based on the different values of certain characteristics that have been observed and reported both for oil spills and look-alikes. Dark spot detection has been done using the segmentation methods called Otsu method. Once the dark spots detected, then the features of the detected spots are extracted and classified to discriminate oil spills and look-alikes. Neural networks have been employed to process remote sensing images and have achieved improved accuracy compared to traditional statistical method. However, this method improved by using a classification algorithm called Back Propagation Algorithm for oil spill identification in low-resolution images, is now operative and completely automatic monitoring system.

The remainder of the paper is organized as follows; section 2 describes existing methodology, while section 3 describes the proposed methodology. Experimental results and discussions are drawn in section 4 and section 5 presents conclusion.

## **2. Materials and Methods**

### **2.1. Existing Methodology**

Cost effective satellite oil spill detection systems have been studied for approximately two decades. The disadvantages of optical sensors, including the absence of any clear discriminating feature between oil spills and the surrounding sea and the unavailability of data at night or in bad weather conditions, do not apply to Synthetic Aperture Radar (SAR) sensors. A typical SAR-based oil-spill detection process consists of three stages: image segmentation, feature extraction and classification. The segmentation stage identifies the candidate features within the imagery through a binary classification of image pixels. A feature dataset is then formed by extracting contiguous features from the segmented image and deriving a quantitative description of the shape and form of each feature. The final classification stage uses the feature vector information to segregate oil spills from look-alikes.

The image segmentation was performed using the adaptive thresholding technique. The output of the segmentation stage is a binary image separating dark objects from the background. The binary images obtained after the segmentation stage are processed to derive the boundaries of each object. The next stage involves the generation of a vector of features that quantitatively describe relevant characteristics of the object. SAR images are converted to binary images to segregate dark spots from the background. From this segmented binary image, feature parameters are extracted.

In the final processing stage, a K Nearest Neighbors' classifier was used to distinguish oil spills from lookalikes based on the feature vector describing each dark object. The neighbors are taken from a set of objects for which the correct is known. This can be thought of as the training set for the algorithm, though no explicit training step is required. The  $k$ -nearest neighbor algorithm is sensitive to the local structure of the data. Using this classification method oil spill classification is done.

## 2.2. Proposed Methodology

In the proposed work, the development of a new approach to SAR oil spill detection using Otsu method and Artificial Neural Networks has been developed. A SAR-based oil-spill detection process consists of three stages; they are dark spot detection, dark spot feature extraction and dark spot classification. Figure 1 shows the oil spill detection system.

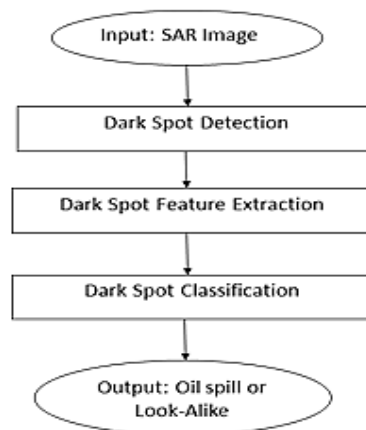


Figure 1: Oil Spill Detection System

### Dark Spot Detection

The dark spot detection involves segmentation of images [3]. The image segmentation was performed using the segmentation technique called Otsu thresholding. It is used to perform automatically clustering based image thresholding or the reduction of gray-scale image to binary image. Therefore, the output of the segmentation stage is a binary image separating dark object from the background. The algorithm for Otsu method is given.

### Algorithm for Otsu method

Step 1: Start

Step 2: Read the input SAR image (either oil spill or look-alike images).

Step 3: Reshape the image from 2D gray-scale to 1D image.

Step 4: Find the histogram of the image.

Step 5: Initialize a matrix with values from 0 to 255.

Step 6: Find the weight, mean and the variance for the foreground and background of the image.

Step 7: Compute result =  $(w_{bk} * var_{bk}) + (w_{fg} * var_{fg})$ .

Where  $w_{fg}$  is a weight of foreground,  $var_{fg}$  is a variance of foreground,  $w_{bk}$  is a weight of background and  $var_{bk}$  is a variance of background.

Step 8: Obtain the minimum value from the result.

Step 9: Finally, convert the image to binary with the calculated threshold value to get the segmented image.

Step 10: Stop.

### Dark Spot Feature Extraction

Features are very important for the classification because they are used as inputs to the classifier. Therefore, the combination of features which discriminate oil spills from the look-alikes is of very high importance for the classifier and for the method's accuracy. In general oil spill detection methodologies traditionally use arbitrary selected quantitative and qualitative statistical features for classifying dark objects on SAR images into oil spills or look-alike phenomena. Table 1 shows the feature parameters extracted from the detected dark spot.

Table 1: Feature Parameters

Category	Features
Gradient Features	Gradient Mean
	Gradient Standard Deviation
	Power to Mean Ratio

In order to determine the most suitable parameters (features) to characterize the slicks, an analysis has been carried out on the gradient features which were used as a feature vector for classifying the dark spots. The combination of features which discriminate the oil spill from the look-alikes is of very high importance for the classifier and for the method's accuracy. The gradient power to mean ratio is used to represent the contrast in the gradient image in quantitative terms.

### Dark Spot Classification

The purpose of the classifier is to differentiate the oil spills from look-alikes. Difficulty intensity of the classification task depends on the variability of the oil spill and look-alike examples [6]. During the training stage classifier learns the patterns from examples and at a later stage it is used to take a decision (classification step). Fig. 2 shows back propagation network with the topology of 3-5-1 neurons.

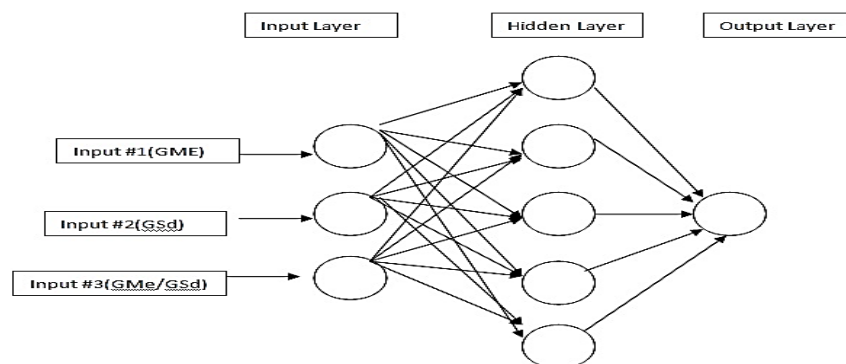


Figure 2: Feed Forward back propagation network

A different classification methodology is presented using artificial neural network to classify the dark formations. Artificial neural network is used as a classifier for the discrimination of oil spill from look-alikes. In this proposed method, back propagation algorithm has been implemented for oil spill classification, with network topology as 3-5-1, namely 3 input neurons, 5 neurons in the hidden layer and 1 output neuron.

### 3. Results and Discussions

In the proposed work, dark spot detection has been carried out by segmenting the spill area using segmentation operation based on Otsu method. Features from the segmented binary image would be extracted, then that feature parameter values were given as an input to the classifier and finally classification technique was implemented using feed forward backpropagation (BPN) algorithm. Finally, testing has been done for finding out the accuracy of classification.

The very first stage of oil spill monitoring system is segmentation operation using Otsu method. The following figure shows the segmentation operation of oil spill and look-alike SAR image.

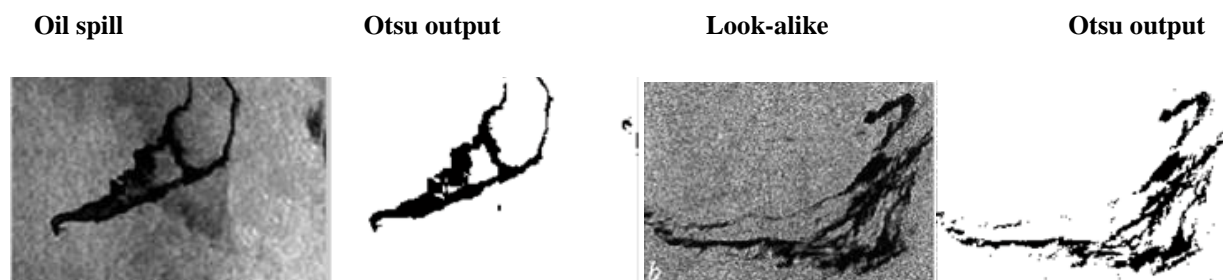


Figure 3: Otsu thresholding technique applied to the oil spill and look-alike SAR image

The next stage was feature extraction operation. In this, features were extracted from each binary image separating dark objects from the background. In order to construct the network architecture, these features parameter values were given as input to the artificial neural network classification. The statistical feature parameters considered for oil spill and look-alike, for the dataset [6] has been shown in table 2.

Table 2: Feature parameters used for oil spill and look-alike cases

Feature Parameter	Look-alike		Oil Spill	
	Min	Max	Min	Max
Grad Mean Spot	0.37	0.86	0.07	0.35
Grad Std Spot	1.05	1.40	0.49	1.00
Grad Power to Mean Ratio	1.63	2.85	2.89	6.47

It was observed from Table 2, that the values for gradient mean, gradient standard deviation and gradient power to mean ratio were varied between the available examples of oil spill and look-alike spots.

In the final stage, ANN based classifier is used to distinguish oil spills from lookalikes based on the three-element feature vector describing each dark spots. The work reveals that BPN network

recognizing the oil spill from look-alike give more accurate values. In all the cases, the 3-5-1 network architecture proved optimal among the other architectures. Fig. 4 shows the training accuracy of the neural network.

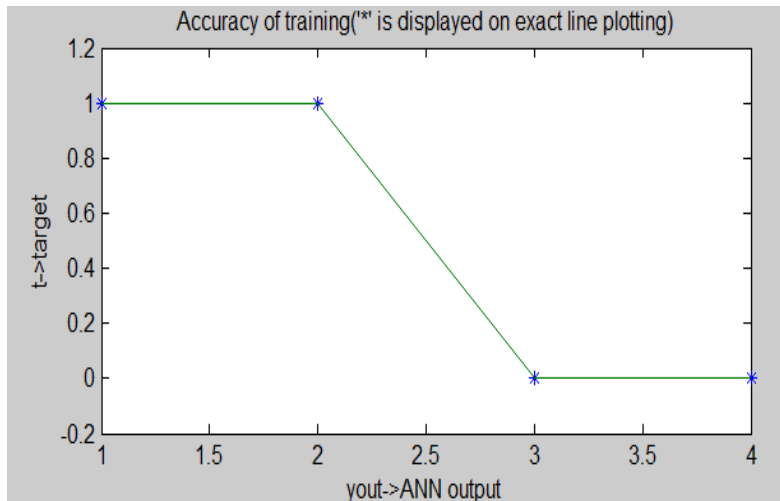


Figure 4: Training accuracy of neural network classifier

Table 3: 20 SAR images used for training

Sample Images	Grad Mean	Grad Std	Power Ratio	Result	Classified
Image 1	0.3289	0.9537	2.8990	Oil spill	Yes
Image 2	0.1039	0.5788	5.5705	Oil spill	Yes
Image 3	0.1904	0.7686	4.0358	Oil spill	Yes
Image 4	0.1419	0.6558	4.6208	Oil spill	Yes
Image 5	0.1930	0.7612	3.9429	Oil spill	Yes
Image 6	0.2687	0.9058	3.3702	Oil spill	Yes
Image 7	0.1201	0.5519	4.5924	Oil spill	Yes
Image 8	0.1247	0.6328	5.0723	Oil spill	Yes
Image 9	0.3832	1.0520	2.7448	Look Alike	Yes
Image 10	0.1475	0.6807	4.6134	Oil spill	Yes
Image 11	0.1898	0.7727	4.0712	Oil spill	Yes
Image 12	0.2751	0.9111	3.3113	Oil spill	Yes
Image 13	0.3717	1.0535	2.8343	Look Alike	Yes
Image 14	0.2120	0.8059	3.8010	Oil spill	Yes
Image 15	0.0766	0.4955	6.4675	Oil spill	Yes
Image 16	0.3032	0.9558	3.1515	Oil spill	Yes
Image 17	0.1071	0.5851	5.4594	Oil spill	Yes
Image 18	0.8573	1.4000	1.6329	Look Alike	Yes
Image 19	0.2587	0.8876	3.4305	Oil spill	Yes
Image 20	0.2940	0.9336	3.1755	Oil spill	Yes

Table 4: Testing of 15 SAR images after training

Sample Images	Grad Mean	Grad Std	Power Ratio	Result	Classified
Image 1	0.1614	0.6986	4.3279	Oil spill	Yes
Image 2	0.5594	1.2285	2.1960	Look Alike	Yes
Image 3	0.1493	0.6850	4.5875	Oil spill	Yes
Image 4	0.1892	0.7732	4.0856	Oil spill	Yes
Image 5	0.1644	0.7052	4.2883	Oil spill	Yes
Image 6	0.2199	0.8265	3.7576	Oil spill	Yes
Image 7	0.1495	0.6895	4.6105	Oil spill	No
Image 8	0.2257	0.8022	3.5531	Oil spill	Yes
Image 9	0.7573	1.3266	1.7515	Look Alike	No
Image 10	0.2619	0.9012	3.4404	Oil spill	Yes
Image 11	0.1344	0.6550	4.8719	Oil spill	Yes
Image 12	0.4166	1.0992	2.6386	Look Alike	Yes
Image 13	0.2382	0.8083	3.3922	Oil spill	Yes
Image 14	0.1451	0.6688	4.6063	Oil spill	Yes
Image 15	0.2219	0.8220	3.7032	Oil spill	Yes

The developed system has been applied and tested with thirty five ESA and ENVISAT SAR images, which are available from the CEARAC SAR image database [6]. The above tables (Table 3 and Table 4) show training and testing of oil spill and look-alike SAR images in classification. So, it has been found that artificial neural network based on Backpropagation algorithm achieves the optimal result in discriminating oil spill from look-alike, since most of SAR images are correctly classified. The overall success rate of BPN network is shown in table 5.

Table 5: BPN Success Rate

Category	Classification Result		
	Correctly Classified	Mis-Classified	Success Rate
Oil Spill	28	1	96.5 %
Look-alike	5	1	83 %

Table 6: Comparison between Existing Work and Proposed Work

Category	K Nearest Neighbors Algorithm	Back Propagation Algorithm
Number of Images	30	35
Success Rate	86%	94%

From table 6, comparison between K nearest neighbor algorithm and Back propagation algorithm shows that the BPN algorithm gives better result than the K Nearest Neighbors algorithm, in the case of accurate classification of segmented dark objects. Fig. 5 and Fig.6 shows a sample output of the classification using Artificial Neural Network classifier.



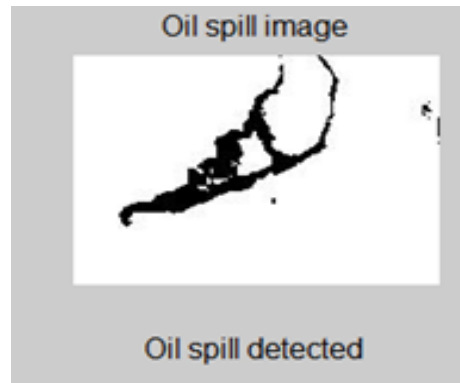


Figure 5: Final classification of oil spill through ANN training

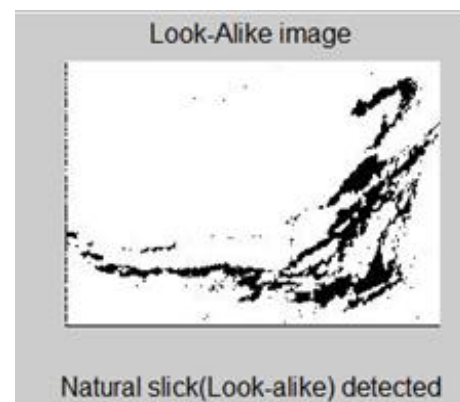


Figure 6: Final classification of look-alike through ANN training

#### 4. Conclusion

In the proposed method, an oil spill detection algorithm was implemented by hybridizing Otsu method and artificial neural network technique. The presented algorithm can distinguish between oil spills and look-alikes. The experimental results demonstrate that the proposed segmentation algorithm has the ability to detect the dark spot correctly and neural network was used as a classifier for discriminating the oil spills from look-alikes. Oil spill classification accuracies were highly dependent on the feature set selection. Here gradient features were used for the evaluation criteria for classification. The classification stage achieved an accuracy of 94%. Hence, this accuracy of algorithm shows that the system is valuable in order to reduce the amount of images for manual inspection in an operational oil spill detection service. The largest challenge in detection of oil spills in SAR images is accurate discrimination between oil spills and look-alikes. As the system is based on neural network training, the quality of the detection increases with increasing amount of data.

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