NEURAL NETWORK ALGORITHM FOR OIL SPILL AUTOMATIC DETECTION FROM MULTI MODE RADARSAT-1 SAR SATELLITE DATA

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Abstract: The main objective of this work is to utilize automatic detection algorithm for oil spill pixels in multimode (Standard beam S2, Wide beam W1 and fine beam F1) RADARSAT-1 SAR satellite data and ENVISAT ASAR that were acquired in the Malacca Straits, and Gulf of Mexico, respectively. In doing so, neural network (NN) algorithm is implemented for oil spill detection. The results show that NN is the best indicator for oil spill detection as it can discriminate oil spill from its surrounding such as look-alikes, sea surface and land. The NN shows higher performance in automatic detection of oil spill in RADARSAT-1 SAR data with standard deviation of 0.12. In conclusion, NN algorithm is an appropriate algorithm for oil spill automatic detection and W1 beam mode is appropriate for oil spill and look-alikes discrimination and detection. It can also said that ASA-APP-1P imagery with HV polarization provided better detection of oil spill using neural network algorithm.

INTRODUCTION

It is well known that oil spill pollution disaster can be occurred every year due to tanker rupture, illegal oil discharges by ships or natural oil seepage. Therefore, marine oil spill pollutions are difficult to be controlled because of the impacts of other factors such as weather, currents, tides, and many chemical and physical factors (like the presence of icebergs). These factors accelerate the rapid spreading of oil spill over short period with large scale distance of 100 km. This was illustrated at Deepwater Horizon oil spill in the Gulf of Mexico, Sunday, July 11, 2010 (Figure 1).

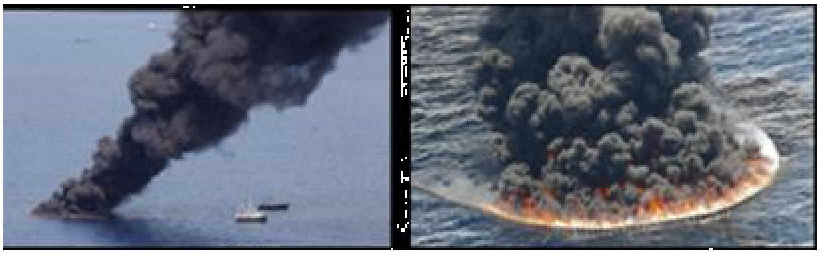

Figure 1: Deepwater Horizon oil spill in the Gulf of Mexico

According to Marghany and Mazlan (2011), standard procedures are necessitated for oil spill monitoring and detection in multi SAR data to guarantee the coastal zone clean up management to avoid damage to marine ecosystem. Therefore, the international oil companies are scattering world wide can acquire the benefits of utilizing multiSAR data as main tool for early warning system for marine oil pollutions. In fact, the Synthetic Aperture Radar (SAR) instrument, which can gather data autonomously of meteorological conditions such as heavy cloud covers and during day and night. This makes SAR as an tremendous tool to track and detect oil in ocean surface. Nevertheless, the disadvantage of SAR is can not distinguish between oil spill and look-alikes. This is because both are appeared as dark patches on SAR images due to the damping impact of the oil on the SAR backscattered signals from the radar antenna (Marghany and Genderen 2001; Brekke and Solberg, 2005, Topouzelis, 2008). In this paper, we address the question of utilization MultiSAR data for monitoring oil spill disasters from space. In fact, there are several factors could be impact the accuracy of oil spill detection such as sensor type, wind speed (> 3 m/s) (Migliaccio et al., (2007) and Topouzelis et al., 2008), discrimination between oil spill, look-alikes and wind shadow zone. Previous studies have used single data set which is not adequate to deliver any accurate decision regarding implementation of different texture algorithms for oil spill detection (Marghany and Genderen 2001). This work has hypothesized that the dark spot areas (oil slick or look-alike pixels) and its surrounding backscattered environmental signals in the SAR data can be detect by using neural network. In this context, neural network (NN) can be used as a automatic tool to discriminate between oil spills, look-alikes and surrounding sea surface waters. In doing so, this study is extended the previous work done by Marghany (2001) and Marghany and Genderen (2001), use the RADARSAT-1 SAR different beam mode data i.e., Wide beam mode (W1) and Standard beam mode (S2) to compare to compared with ASA-APP-1P with HV polarization.

METHODS AND EQUATION

Study Area

Following Marghany and Hashim (2011), the study is carried out along the Malacca Straits coastal waters. The Strait of Malacca is located between the east coast of Sumatra Island in Indonesia and the west coast of Peninsular Malaysia, and is linked with the Strait of Singapore at its south-east end (Figure 2). The Strait of Malacca is bordered on the north-west by a line from Ujung Baka (5°40 ′N, 95°26′ E),the north-west extremity of Sumatra, to Laem Phra Chao(7°45 ′N,98°18 ′E),the south extremity of Ko Phukit Island, Thailand and on the south-east by a line from Tahan (Mount) Datok (1°200′ E,104°20′ N) and Tanjung Pergam (1°100′ E, 104°20′ N) (Hamzah, 1988; Marghany 2001).

Figure 2: Location of Study Area (source: http://www.welt-atlas.de/map_of_strait_of_malacca_6-847).

Data Acquisition

The SAR data acquired in this study are from the RADARSAT-1 SAR that involves Standard beam mode (S2); W1beam mode (F1) image (Table 1). SAR data are C-band and have a lower signal-to noise ratio due to their HH polarization with wavelength of 5.6 cm and a frequency of 5.3 GHz. Further, RADARSAT-SAR data have 3.1 looks and cover an incidence angle of 23.7° and 31.0° (Marghany et al., 2009a, b). In addition, RADARSAT-SAR data cover a swath width of 100 km. According to Mohamed et al.,(1999); Marghany (2001) Marghany (2004); Marghany et al., (2009a, b) oil spill occurred on 20 December 1999, along the coastal water of Malacca Straits (Marghany and Hashim 2010).

Table 1: RADARSAT-1 SAR Satellite Data Acquisitions

Mode Type	Resolution (m)		Incident Angle(^{o})	Looks	Swath width (km)	Date
	Range	Azimuth				
W1	182.437	150.000	20° - 5°	1 x 4	100 km	1997/10/26
S2	111.662	110.037	20° - 41°	1 x 4	100 km	1999/12/17
F1	113.675	137.675	37° - 49°	1 x 1	50 km	2003/12/11

Neural Network Algorithm

Following Frate et al., (2000) and Marghany and Hashim (2011), the simplification of artificial intelligence neural network concept can be represented in Figure 3. There are three layers are involved within neural network (i) input layers;(ii) neural network core processing; and (iii) decision out put layer.

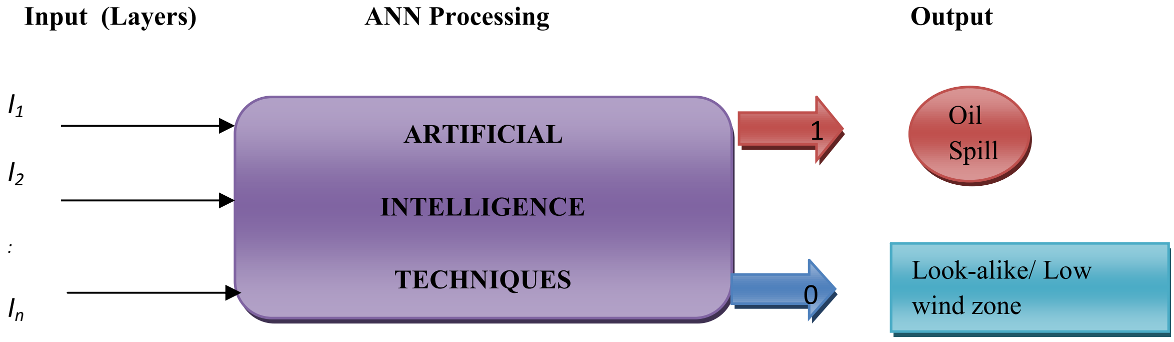

Figure 3: Simplification of neural network concept

I_1,I_2 and I_n are assumed as input layers information that are retrieved from multi-SAR data of different dark patch pixels and their surrounding pixels (Figure 4). The input layers can include wind speed; statistical description of physical features and Geometrical features. Therefore, the output is the automatic level detection in the range between 0 and 1. In this context, oil spill pixels are represented by 1 while look-alikes or wind low zone pixels are represented by 0. The neural network (NN)-based pattern-recognition approach for Static Security Assessment (SSA) depends on the assumption that there are some characteristics of pre-contingency system states that give rise to oil spill occurrences in RADARSAT-1 SAR data which is represent post-contingency system**.** The task of the NN is to capture these common underlying characteristics for a set of known operating states and to interpolate this knowledge to classify a previously unencumbered state. The first step in such an application is to obtain a set of training data which represents the different backscatter value variations in RADARSAT-1 SAR data (Topouzelis et al., 2008). Following, Hect-Nielsen (1989) and Topouzelis et al., (2009), the ANN's and the pattern recognition (PR) technique, feed forward network with back-propagation algorithm are used in this study for both static and dynamic security assessment. For this application, a multi-layer feed forward network with error back-propagation has been employed (Aggoune et al., 1989). The major steps in the training algorithm are: Feed forward calculations, propagating error from output layer to input layer and weight updating in hidden and output layers (Frate et al.,2000). Forward pass phase calculations are shown by the following equations between input (*i*) and hidden (*j*) (Michael, 2005 and Topouzelis et al., 2009).

$$\theta_j = \frac{1}{1+e^{(\sum_j w_{ij}\theta_i + \theta_j)}} \qquad (1)$$

$$\theta_k = \frac{1}{1+e^{(\sum_k w_{jk}\theta_j + \theta_k)}} \qquad (2)$$

where θ_j is the output of node *j*, θ_i is the output of node *i*, θ_k is the output of node w_{jk} is the weight connected between node *i* and *j*, and θ_j is the bias of node *j*, θ_k is the bias of node *k*. In backward pass phase, error propagated backward through the network from output layer to input layer as represented in equation (Michael, 2005). Following Topouzelis et al., (2009), The weights are modified to minimize mean square error (MSE).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=a}^{m}(d_{ij} - y_{ij})^2 \qquad (3)$$

where d_{ij} is the j^{th} desired output for the i^{th} training pattern, and y_{ij} is the corresponding actual output. More details of the mathematical procedure are available in Michael (2005).

RESULTS AND DISCUSSIONS

Figure 4 shows dark patches are clear in different mode of RADARSAT-1 SAR data W1,S2, and F1 respectively. It is difficult to judge which patches belong to oil spill because the speckle impact and confusing likeness between oil spill pixels and other dark pixels which could be look-alike or low wind zone area. In fact, different variation of backscatter in single SAR data or multi-SAR produce high level of complexity in SAR data. In addition, this complexity is because of also damping of radar backscatter in the sea surface. Therefore, existence of oil spills or look-alikes (Alpers and Hühnerfuss 1988 and Trivero et al., 1998) which significantly decrease the measured backscattering energy resulting in darker areas in SAR imagery.

(a) **(b)** **(c)**

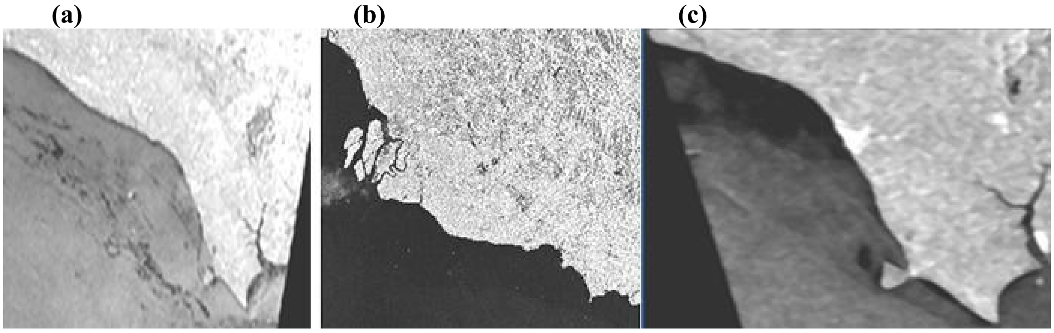

Figure 4: MultiRADARSAT-1 SAR different mode data (a) W1, (b) S2 , and (c) F1 respectively

Figure 5 shows the output results of neural network. Clearly, neural network algorithm is able to isolate oil spill dark pixels from the surrounding environment. In other words, look-alikes, low wind zone, sea surface roughness, and land are marked by white colour while oil spill pixels are marked all black. Figure (5b) does not show any class presence or existence of oil spill event. Further, Figure 5 shows the results of the Artificial Neural Net work, where 99% of the oil spills in the test set were correctly classified. Three scenes by the leave-one-out method presented an exact classification of 99 % for oil spills (an approach based on multilayer perceptron (MLP) neural network with two hidden layers). The net is trained using the back-propagation algorithm to minimize the error function. 99% of oil spills are automatically detected using the leave-one-out method. This study agrees with study of Topouzelis et al., (2009).

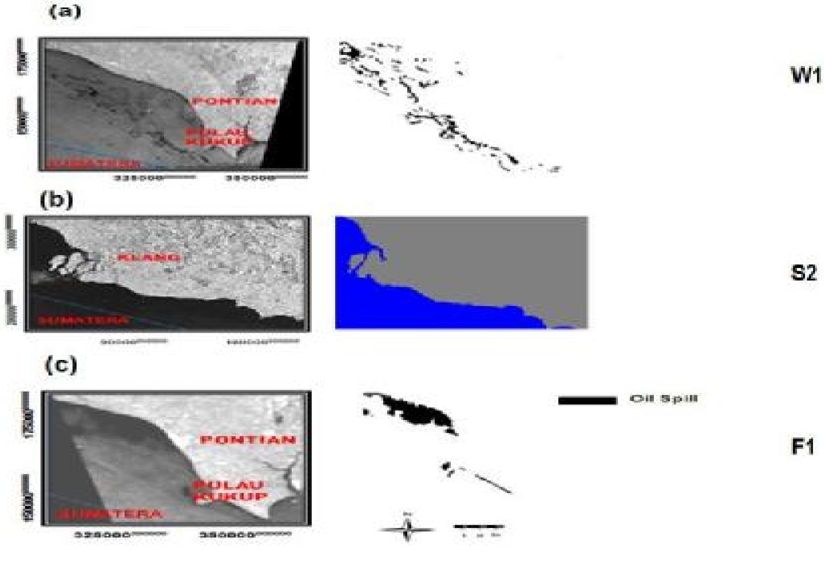

Figure 5: Neural network results for (a) (a) W1, (b) S2 , and (c) F1 respectively

Figure 6 shows the similar output has been achieved in ENVISAT ASAR data for the Deepwater Horizon oil spill disaster which occurred in the Gulf of Mexico, May 9 2010. Figure 7 shows the comparison between different multi mode data of RADARSAT-1 SAR and ENVISAT ASAR data. The lowest error standard deviation of 0.002 occurs in W1 mode data. This means that W1 performs better detection for oil spill as compared to S1 and S2 mode data. In fact, W1 shows steeper incident angle of 30° than both F1 and S2 mode data.

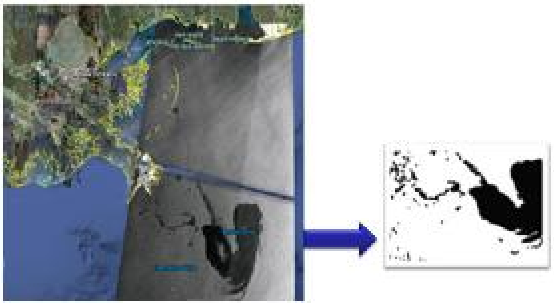

Figure 6: Neural network output for ENVISAT ASAR data in Gulf of Mexico, May 9 2010

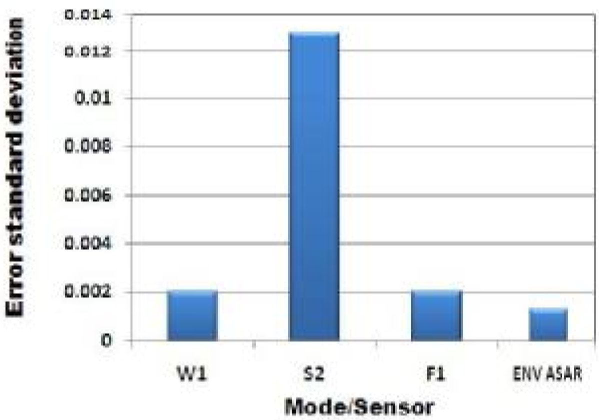

Figure 7: Accuracy of different mode RADARSAT-1 SAR and ENVISAT ASAR

Generally, ENVISAT ASAR has standard error smaller than RADARSAT-1 SAR data for oil spill detection by neural network. It is found that ASA-APP-1P imagery with HV polarization allowed better discrimination off oil slick than HH polarization. Further more, steeper Incident angle 20° with swath cover of 400 km and geomateric resolution of 150 m allowed excellent tracking and detection as compared to RADARSAT-1 SAR. This study is consitented with Topouzelis et al., (2009). In consequence, the ANN extracted oil spill pixels automatically from surrounding pixels without using thresholding technique or different segemntation algorithm as stated at Solberg et al., (1999); Samad and Mansor (2002); Topouzelis et al., (2007);Marghany and Hashim (2010).

CONCLUSION

This study has demonstrated a method based on neural network algorithm for oil spill automatic detection from different RADARSAT-1 SAR different mode data and ENVISAT ASAR satellite data. Three RADARSAT-1 SAR different mode of W1,S2, and F1,respectively are used in this study and compared with ASA-APP-1P with HV polarization. The study shows that ANN provide excellent automatic oil spill detection with error of standard deviation of 0.12. It is found that ASA-APP-1P imagery with HV polarization allowed better discrimination off oil slick than HH polarization.

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