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Comparisons of different semi-automated techniques for oil spill detection: A case study in Lebanon

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ABSTRACT: Today, oil spills in the marine environment originated from land-based or sea-based sources are growing in all countries around the world and have serious biological and economic impacts. One of the most dangerous and hazardous effects on marine environment is the discharge of oil including with the tanker accidents. Besides oil pollution occurred recently in the Lebanon coast is one of the most hazardous land-based threats in the eastern Mediterranean coasts with an estimation of 110,000 barrels of oil. Due to not enough cleaning activities carried on, the oil pollution has spread 100 miles along the coast and effected also to Syria's shoreline. Depending on the wind and current condition, the spilled oil could also be a big threat to other neighborhood countries such as Turkey, Greece, and Cyprus.

In order to interfere the oil spill, it is important to identify the type, areal extent, position, (nearest ship position if any), the possibility percentage etc. For this purpose, satellite-based oil pollution monitoring systems are being used to take precautions and even to determine the possible polluter. Today, Synthetic Aperture Radar (SAR) satellites are often preferred to optical sensors due to the all-weather and all-day capabilities and being used to detect the oil spills discharged into the sea with sufficient accuracies.

In this study, Radarsat-1 images covering Lebanon coasts acquired by ITU-CSCRS (Istanbul Technical University – Center of Satellite Communication and Remote Sensing) during the event were evaluated using both visual analysis and semi-automatic image processing techniques based on Artificial Intelligence. The urgent need for the establishment of an operational satellite-based oil spill monitoring system in the area and the effective role of a ground receiving station at ITU were also outlined.

1 INTRODUCTION

The increase and development in the marine transportation began to be an important factor for the oil pollution of maritime environment both socially and economically. Oil pollution can effect the environment by many different ways, such as major disasters at sea, and illegal tank cleaning or bilge pumping that has more chronicle results (Bava *et al.*

2002, Harahsheh *et al*. 2004). The amount of oil spilled annually worldwide has been estimated at more than 4.5 million tons (Bava *et al*. 2002). Illegal oil spills at sea occur during tanker and cargo ship operations, where ballast waters, tank washing residues, fuel oil sludge and machinery space bilge deliberately are discharge into the sea (Maar *et al.* 2003).

The %30 of international marine trade takes place among the ports of Mediterranean and nearby seas. As the world's %28 of the petroleum transport passes through Mediterranean the %50 of the total transportation is considered to be risky and dangerous. Every year nearly 20.000 tons of petroleum leaks to Mediterranean from the surrounded 60 oil refining plants as a result of consciously or unconsciously accidents (Günel 2004).

In major case of discharged oil to the seas such as the latest one occurred at Lebanon coasts, the detection and monitoring of the oil spills have critical importance for rapid emergency response activities. These should cover four basic issues; *i)* prevention *ii)* alarm, *iii)* monitoring and *iv)* damage quantification (Bava *et al*. 2002). Whatever its source is, oil spill pollution will continue to occur, therefore, in order to lessen its effect, the improvement of its detection and continuous monitoring are the most important issues to effectively plan countermeasures responses. In this aspect, urgent need for the establishment of an operational satellite-based oil spill monitoring system in the Turkish and Northern Cyprus's territorial waters and the importance of the ground receiving station at ITU, the first ground receiving station dedicated to remote sensing in Turkey, to establish and use such a system effectively must be understood.

2 STUDY AREA AND DATA USED

As one of the East Mediterranean countries, Lebanon, neighboring Syria and Israel, has 225 km coastline. The most recent oil pollution that occurred due to the bombing of a power plant at Jieh, 12 miles south of Beirut, has approximately affected 1/3 of the whole Lebanese coastline, nearly 70–80 km north of the power plant. Depending on the weather conditions, it could be also a serious threat to the neighboring Mediterranean countries such as Turkey, Cyprus and Syria. Among them, Northern Cyprus, 162 km away from Lebanon, has a length of approximately 330 km coastline with up to 12 km

Table 1. The characteristics of the radar dataset used.

Satellite	Acquisition date	Beam mode	Spatial resolution (m)	Band	Wavelength (cm)	Pol.	Coverage (sq km)
RADARSAT-1	2006-07-21	Fine	8	C	5.3	HH	50 × 50
	2006-08-09	Standard	25				75 × 75
	2006-08-17	Wide	30				150 × 150
	2006-08-23	Standard	25				75 × 75
	2006-10-01	Fine	8				50 × 50

nautical miles of territorial waters (Sunar *et al.* 2007). In this study, as an active sensing system, 5 of total 20 Radarsat-1 images acquired by ITU-CSCRS were used in the analyses (Table 1).

3 METHODOLOGY

Oil slicks on sea can be detected because of the dampening effect of oil on capillary waves. Therefore radar images have an advantage for oil spill detection at this point where oil can be detectable as black patches on images. In general there are three different techniques for oil spill detection; *i)* manual detection; *ii)* semi-automated detection; and *iii)* fully-automated detection. In this study, semi-automated method was used and four methods explained briefly below were tested.

3.1 *Maximum likelihood classification (ML)*

The maximum likelihood classifier is one of the most popular methods of classification in remote sensing, in which a pixel with the maximum likelihood is classified into the corresponding class. The likelihood L_k is defined as the posterior probability of a pixel belonging to class k. For mathematical reasons, a multivariate normal distribution is applied as the probability density function.

3.2 *Artificial neural netwok (ANN)*

Artificial neural networks are computational systems based on the principles of biological neural systems, i.e. it is a mathematical model composed of many neurons operating in parallel. These networks have the capacity to learn, memorize and create relationships amongst data. They have some advantages such as their non-parametric and non-linear nature, arbitrary decision boundary capabilities, easy adaptation to different types of data and input structures, and good generalization capabilities over classical statistic and analytic approaches. Although the network design as a classifier is a hard task despite the increment in the performance of classification, an approach for oil spill detection based on a Multilayer Perceptron (MLP) neural network are described in recent research studies (Frate *et al.* 2000), (Topouzelis *et al.* 2005).

3.3 *Adaboost classification (ADABOOST)*

Boosting (Schapire 1990) is an ensemble method used for increasing the precision of a weak or base classifier based on the principle of divide-and-conquer (Ramalho & Medeiros 2006). An ensemble is a set of classifiers whose individual predictions are combined to classify new examples (Dzeroski & Zenko 2004) with better performance than using a single classifier. These individual classifiers called as weak or base classifiers can be decision tree, perceptron learning rule, binary thresholding a single feature, etc. The original boosting algorithm was improved to get adaptive boosting

(ADABOOST) (Freund & Schapire 1997). The coding flowchart and some theories can be found in Freund & Schapire (1999), Schapire & Singer (1999) and Ramalho & Medeiros (2006).

3.4 *Adaptive neuro-fuzzy inference system (ANFIS)*

Neuro-fuzzy systems are hybrids of fuzzy systems and neural networks (Jang *et al.* 1997). The goal of neuro-fuzzy systems is to combine the learning capability of a neural network with the intuitive representation of knowledge found in a fuzzy system. ANFIS based on Sugeno type fuzzy inference system (FIS) uses a hybrid learning algorithm to identify the membership function parameters of single-output. The membership functions used in ANFIS can be Simple Gaussian, Generalized Bell Curve, 2-Sided Gaussian, Triangular, Trapezoidal, Sigmoid Curve and S-Shape Curve. In ANFIS, the membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone, or in combination with a least squares type of method using a given set of input/output data. Some of the advantages of ANFIS are very fast convergence due to hybrid learning and the ability to construct reasonably good input membership functions. The most important advantage is that ANFIS provides more choices over membership functions (Garzon *et al.* 2002). The detailed information about neuro-fuzzy systems can be found in Pal & Mitra (1992) and Takagi & Sugeno (1985).

4 APPLICATION AND RESULTS

In general, SAR data are subject to speckle which is a natural phenomenon generated by coherent processing of radar echoes. Therefore the radar images were firstly filtered by a 3×3 median and 5×5 low-pass convolutions, respectively for speckle noise reduction. After filtering, co-occurrence texture measurements were computed (Haralick *et al.* 1973). Because of the coherent nature of SAR imaging, these measures are more suitable for classification instead of using individual pixel brightness values. In contradiction to the pixel intensity itself, texture provides information about the spatial correlation among neighboring pixels. From these measures, homogeneity, angular second moment (Assilzadeh & Mansor 2001), variance and mean were found effective in discrimination of oil spills from other features at the sea surface. These grey level co-occurrence matrixes (GLCM) based textural features were computed using 5×5 kernels. Consequently, the input data dimension is set as four, the number of classes is two of oil and alike.

The patterns from which these textural values computed were totally collected from 5 different RADARSAT-1 images. The training areas were determined by taking into consideration both the meteorological conditions (weather state, wind etc.) and manual visual inspection.

Afterwards, the training patterns were sampled randomly for a reasonable number of patterns to reduce the computational burden from training areas. For each class, 5000 training and 5000 test patterns were separately collected. The classification methods used to determine the oil spill discharged regions in this study are ML, ANN, ADABOOST and ANFIS.

From artificial neural network structures, Multilayer Perceptron was employed. The training algorithm used for updating the synaptic weights and bias values was selected as Resilient Backpropagation (Reidmiller & Braun 1993). This learning algorithm was found as the best from a test sequence of different learning rules such as standard gradient decent with momentum, conjugate gradient methods and one-step secant. The network topology was constituted as an input layer, two hidden layers and an output layer. The numbers of neurons of these layers were 4 for input layer, 50 for first hidden layer and 50 for second hidden layer and 2 for output layers. Each input layer neuron represents each textural features and each output layer neuron represents the classes, i.e. oil and alike.

ADABOOST method used in this study employs a decision tree classification as a weak classifier (Vezhnevets 2006). The split number for decision tree and boosting iteration number were chosen as 3 and 100 respectively. For boosting method, the only parameter that must be tuned is iteration number. From testing of different iteration numbers, this parameter was set as 100.

In ANFIS application, the number of membership function was set as two and membership function was chosen as Gaussian. Although ANFIS is not a natural classifier, it can be used for a binary classification problem as shown in this study. The output values can be categorized with respect to their signs.

The classification results of the test data from ML, ANN, ADABOOST and ANFIS were given as Tables numbered 2, 3, 4 and 5. In these tables, the abbreviations of PA, UA and OA mean producer accuracy, user accuracy and overall accuracy. In addition to overall accuracy, the test of hypotheses based on Z-test was done with respect to the Kappa and Z statistics values (Congalton & Green 1999). The significance level was considered as 0.05. In the first test, Kappa statistics was individually tested for evaluating the difference of the algorithmic classification from a random one. The second test was

Table 2. ML classification.

	Oil	Alike	Total	UA
Oil	2714	733	3447	78.7
Alike	2286	4267	6553	65.1
Total	5000	5000	10000	
PA	54.3	85.3		**OA = 69.8**

Table 3. ANN classification.

	Oil	Alike	Total	UA
Oil	3311	521	3832	86.4
Alike	1689	4479	6168	72.6
Total	5000	5000	10000	
PA	66.2	89.6		**OA = 77.9**

Table 4. ADABOOST classification.

	Oil	Alike	Total	UA
Oil	3348	655	4003	83.6
Alike	1652	4345	5997	72.5
Total	5000	5000	10000	
PA	67.0	86.9		**OA = 76.9**

Table 5. ANFIS classification.

	Oil	Alike	Total	UA
Oil	3090	506	3596	85.9
Alike	1910	4494	6404	70.2
Total	5000	5000	10000	
PA	61.8	89.9		**OA = 75.8**

done to see how well the classification methods differ from each other. The Kappa and Z statistics values and variance values were given in Tables 6 and 7, respectively.

Test 1:
H_0:$Kappa_1 = 0$, H_1:$Kappa_1 \neq 0$ and the rejection region R: $|Z| \geq z_{\alpha/2}$
For α significance level of 0.05, R: $Z \geq 1.96$ or $Z \leq -1.96$
The test statistics, $Z = Kappa_1/\sqrt{Var(Kappa_1)}$

Test 2:
H_0:$(Kappa_1–Kappa_2) = 0$ and H_1:$(Kappa_1–Kappa_2) \neq 0$ and the rejection region R: $|Z| \geq z_{\alpha/2}$
For α significance level of 0.05, R: $Z \geq 1.96$ or $Z \leq -1.96$
The test statistics, $Z = (|Kappa_1 - Kappa_2|)/\sqrt{Var(Kappa_1) + Var(Kappa_2)}$

Table 6. Kappa, Z statistics and variance values.

	Kappa(%)	Variance of Kappa	Z-statistic	Std of OA
ML	39.62	0.00007617	45.40	0.00450
ANN	55.80	0.00006511	69.16	0.00409
ADABOOST	53.86	0.00006817	65.23	0.00418
ANFIS	51.68	0.00006751	62.90	0.00421

Table 7. Pair-wise Z-test values.

	ML	ANN	ADABOOST	ANFIS
ML	–	13.61	11.85	10.06
ANN	13.61	–	1.68	3.58
ADABOOST	11.85	1.68	–	1.87
ANFIS	10.06	3.58	1.87	–

5 CONCLUSIONS

Remote sensing and satellite data are effective tools for man-made hazards like illegal oil spill discharges that need a synoptic view when there is an emergency status and where on site surveying is not possible. Another very important aspect of remote sensing is the production of the near-real time data by operational satellite-based systems so that authorities can quickly and directly use it. One of the most critical data to be supplied is the position of the possible oil spill and its probability level (i.e. low, medium or high). Since this information will be used for the response crews in a short enough time following an oil spill incident, the accuracy of the detection has an importance.

As shown in this study, four different classifiers were used for detection of oil spills. It was seen that the classification matrixes of all classifiers are better than random, i.e. rejection of null hypothesis. Based on the second test, maximum likelihood classification matrix is significantly different from others. ADABOOST method is not significantly different from both ANN and ANFIS statistically. But the strength of the significance evidence of ANN vs. ADABOOST is higher than ANFIS vs. ADABOOST. Despite being a new method as a classifier, these results should encourage to use ANFIS for oil spill detection. But its effectiveness must be deeply examined for different case studies. As a general conclusion, ANN was found the most efficient method for determination and identification of oil spill discharged areas.

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