Feature Extraction And Classification Of Oil Spills In Sar Imagery

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Abstract

Synthetic Aperture RADAR (SAR) imaging system is used to monitor the marine system. Oil spill pollution plays a significant role in damaging marine ecosystem. One main advantages of SAR is that it can generate imagery under all weather conditions. In a SAR image dark spots can be generated by number of phenomena. The dark spots may be of algae, low wind areas, coastal areas and oil spills. The detected dark spots are then classified based on the features. The features of dark spot are extracted to discriminate oil spill from look-alikes. The textural and statistical features are extracted and analyzed for oil spill identification. This paper discusses about the different feature extraction and classification method for oil spill detection and their preliminary results.

Keywords: *oil spill, SAR, features, detection, classification, look-alikes.*

1. Introduction

Oil spills seriously damage the marine ecosystem and cause political and scientific concern since they have serious effects on fragile marine and coastal ecosystems. The amount of pollutant discharges and associated effects on the marine environment are important parameters in evaluating sea water quality. Illegal discharges from ships can indeed be eliminated by the strict enforcement of existing regulations and the control, monitoring and surveillance of maritime traffic. Several studies aiming at oil spill detection using SAR images have been implemented [1-5]. Any formation on the image which is darker than the surrounding area has a high probability of being an oil spill and needs further examination.

Although this process seems to be simple for a human operator, it contains three main difficulties if semi-automated or automated methods are used. First, fresh oil spills are brighter than older spills, thus cannot be easily discriminated. Second, areas surrounding dark areas can have various contrast values, depending on local sea state, oil spill type and image resolution. Third, other phenomena may appear as dark areas. Further classification of the dark areas to oil spills and look-alikes is the focus of this work.

Many research works are focused on the development of automated or semi-automated systems for oil spill detection are reported in literature. Kubat et al. (1998) developed a neural network for the classification of dark regions detected in a series of nine SAR images that served as a training set of the system. The complexities of such a system as well as the appropriate actions that have to be taken into consideration by potential tool developers in such fields were analyzed in detail. Input to the classifier was straightforward, though image preprocessing was not automated.

The classifier had an open architecture of rules so that it could embed user experience in several other fields apart from oil detection. Del Frate et al. (2000) also used neural network architecture for semi-automatic detection of oil spills on SAR images using a set of features characterizing a candidate oil spill as input vector. Solberg and Solberg (1996) and Solberg et al. (1999) produced a semi-automated classifier for oil spill detection, in which the objects with a high probability of being an oil spill were automatically detected. Three different categories of probability (low, medium and high) were recognized.

A rational processing procedure was adopted for 84 SAR images utilized. It involved pixel local thresholding based on wind level information, clustering of small pixel objects or partitioning of large pixel objects based on sizing criteria and feeding each individual cluster to a classifier operating on a stochastic processing basis. Ten different object characteristics were identified and classification was based on a Bayesian inference procedure. Fiscella et al. (2000) developed a stochastic classifier based on Mahalanobis statistical tests and classical compound probabilities.

A preprocessing tool was used in order to extract pixel objects from SAR images and classified them according to statistical criteria implemented on a total of 14 different characteristics of extracted clusters. In the present work a fully automated system for the identification of possible oil spills that resembles the expert's choice and decisions has been developed. The system comprises modules of supplementary operation and uses their contribution to the analysis and assignment of the probability of a dark image shape to be an oil spill. SAR images are read, located, land masked, filtered and thresholded so that the appropriate dark areas are extracted. Candidate oil spill objects are classified to determine the likeness of each individual object to be an oil spill. The output images and tables provide the user with all relevant information for supporting decision-making

The remainder of the paper is organized as follows. Section 2 describes SAR imaging of oil spills and lookalikes, Section 3 describes the feature extraction process. The classification problem is discussed in detail in Section 4, while Section 5 contains the experimental results. Section 6 presents conclusion.

2. SAR images of Oil Spills and Look Alikes

SAR systems are mainly used for monitoring the sea to detect dark formation in the sea, as they are not affected by local weather conditions and cloudiness and occupy day to night. SAR systems detect dark spots on the sea surface indirectly, through the modification dark formations cause on the low wind areas – capillary waves. Several manmade and natural ocean phenomena affect the backscattering of the radar signals. For this reason, a dark formation appears dark on SAR imagery in contrast to the surrounding clean sea.

Dark formations can be oil spills, organic film, low wind areas, areas sheltered by land, wind front areas, rain cells, grease ice, current shear zones, internal waves and upwelling zones.

Dark formation on SAR images is due to decrease of back scattering of the sea surface due to oil films and other natural phenomena. Oil spills are either intentional or accidental. Look –alikes are mostly natural ones. May be due to weather or due to sea organisms.

Data set used are ERS -2 , RADARSAT and ENVISAT Images.

2.1 Feature Extraction Process

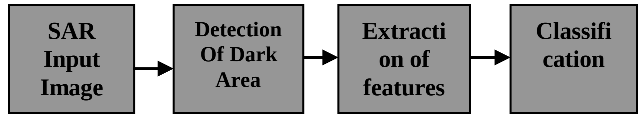
Fiscella et al. (2000) used 14 features for oil spill classification, Solberg and Theophilopoulos (1997) used 15 features. Solberg et al. (1999) used 11 features, many of them different from their previous studies and in general different from the 11 features used by Del Frate et al. (2000). A different approach was given by Espedal and Wahl (1999), in which wind vector data were used and compared with the spreading and length of the dark formations detected. A more general description of the calculated features was given by Espedal and Johannessen (2000), where texture features were introduced for the first time. Moreover, Keramitzoglou et al. (2005) referred to 14 features without presenting them and Karathanassi et al. (2006) used 13 features several studies have tried to unify all the features used with similar characteristics (Brekke and Solberg 2005, Montali et al. 2006).

The absence of systematic research on features extracted and their contribution to the classification results forces researchers to select features arbitrarily as input to their systems. A previous work (Stathakis et al. 2006) was focused on this issue, trying to bridge this gap and to discover the most useful features in oil spill detection. The lack of systematic research can be attributed to the fact that the existing methodologies for searching into a large number of different compilations have not been fully exploited. Genetic algorithms have been successful in discovering an optimal or near-optimal solution amongst a huge number of possible solutions (Goldberg 1989). Moreover, a combination of genetic algorithms and neural networks can prove to be very powerful in classification problems. The methodology of feature selection for oil spill detection is given in Stathakis et al. (2006). The 25 most commonly used features in the scientific community were grouped and their contribution to the final classification was examined. The methodology explores the opportunity of having two unknown parameters in the genetic internal structure, i.e. the number of input features and the number of hidden neurons. The novelty of this approach is the simultaneous evolution of both features and neural network topology. Previously genetic algorithms have been used either to evolve neural network topology (Stathakis and Kanellopoulos 2006) or to select features (Kavzoglou and Mather 2002) but not both at the same time. Thus, a novel synergy of genetic algorithms and neural networks is deployed in order to determine a near-optimal neural network for the classification of oil spills and lookalikes. The present paper evaluates the robustness of the proposed feature combination. In order to further justify the proposed feature combination robustness a comparison with the results of several commonly used reparability indices, including Euclidian, Fisher and Mahalanobis, was performed.

It is very difficult to develop a automatic oil spill detection system as it needs special knowledge to interpret SAR images. Figure 1 shows the steps in detecting the oil spills. The main steps are

1. Preprocess the SAR image to enhance the quality by removing the noise.
2. Detection of Dark areas in SAR Imagery using segmentation process which uses FCM and level Set methods
3. Extraction of Features of Dark Formations
4. Analysis of the feature values by comparing it with oil spill signatures.
5. Classification of dark areas (oil spill or lookalike)

Fig(1) Steps In Detection Of Oil Spills In Sar Imagery



Five features of oil spills are extracted for classification which are basically grouped into the 3 categories. They are based on geometric features, physical features and Contextual features

In pattern recognition, the *k*-nearest neighbours algorithm (*k*-NN) is a method for classifying objects based on closest training examples in the feature space. *k*-NN is a type of instance based learning, or lazy learning where the function is only approximated locally and all computation is deferred until classification. The *k*-nearest neighbor algorithm is amongst the simplest of all matching learning algorithms: an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its *k* nearest neighbors. If $k = 1$, then the object is simply assigned to the class of its nearest neighbor.
The same method can be used for regression, by simply assigning the property value for the object to be the average of the values of its *k* nearest neighbors. It can be useful to weight the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. (A common weighting scheme is to give each neighbor a weight of $1/d$, where'd' is the distance to the neighbor. This scheme is a generalization of linear interpolation.)

2.2 Classification of Dark Area

After spot detection and feature extraction, dark spots are classified as either oil slicks or look-alikes. This is not an easy task, because slick contrast depends on weather conditions, and the probability of observing look-alikes depends on wind level and other external conditions.

2.2.1 *K Nearest Neighbours (KNN) classification*

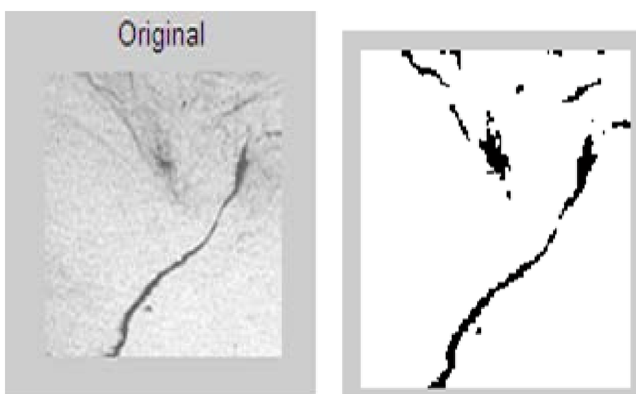
The neighbors are taken from a set of objects for which the correct classification (or, in the case of regression, the value of the property) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required. The *k*-nearest neighbor algorithm is sensitive to the local structure of the data. Using this classification method oil spill classification is done.

3. Experimental Setup and results

The Procedure for classification is described as follows

1. 10 images of each oil spill and look alike are used to form two separate training sets
2. The features like area, perimeter, complexity, shape factor and standard deviation are calculated
3. The values are given as input to the KNN classifier, then the dark area is classified either as oil spill or lookalike based on features.

Sno	Area	Perimeter	Comp lexity	Shape factor	*Std deviation*	classificati on *
Image1	1491	233	0.02	6.04	-1.22	1
Image2	1484	366	0.02	9.16	-3.36	1
Image3	1305	395	0.02	9.68	-0.93	1
Image4	1927	395	0.03	10.72	1.48	1
Image5	1040	342	0.03	8.38	0.97	1
Image6	538	243	0.03	10.40	0.91	1
Image7	2382	634	0.03	30.50	-2.42	1
Image8	1625	595	0.03	5.90	1.09	1
Image9	2196	732	0.04	6.71	1.00	1
Image10	0773	778	0.04	6.95	1.68	1
Image11	5159	582	2.00	3.11	-1.75	2 #
Image12	12823	456	1.13	1.14	-2.00	2
Image13	28074	951	1.6	2.02	0.50	2
Image14	12778	513	1.11	2.70	0.72	2
Image15	25857	692	1.13	1.13	.55	2
Image16	14502	614	1.14	2.35	0.63	2
Image17	34319	1196	1.94	1.22	-0.43	2
Image18	32763	824	1.28	1.83	-0.83	2
Image19	21240	796	1.54	1.84	-0.81	2
Image20	11562	666	1.77	2.39	-0.47	2



(a) Original (b) segmented

4. Conclusions

SAR is the most promising sensor for oil spill detection, as they are not affected by weather conditions. A hybrid method is applied to enhance the image quality. A fusion technique of GMAC with FCM with thresholding is used to detect the dark spots. The features of dark area are extracted. Then they are classified either as oil spill or lookalike. To improve the accuracies more number of features can be considered. The comparison of different classification methods is desirable with same set of data and features.

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