SUPERVISED PATTERN CLASSIFICATION TECHNIQUES FOR OIL SPILL CLASSIFICATION IN SAR IMAGES: PRELIMINARY RESULTS

Andrea Montali[(1)], Giorgio Giacinto[(1)], Maurizio Migliaccio[(2)], and Attilio Gambardella[(1)]

[(1)]*Dip. Ingegneria Elettrica ed Elettronica, Università degli Studi di Cagliari, Piazza D'Armi 19, 09123 Cagliari, Italy.*
[(2)]*Dipartimento per le Tecnologie, Università degli Studi di Napoli Parthenope, Via Acton 38, 80133 Napoli, Italy.*

ABSTRACT
In this study, classical features extracted from Synthetic Aperture Radar (SAR) Images and used in oil spill classification procedures have been examined/evaluated and ranked in function of their effectiveness. The best features have been used to perform the classification of dark patches by means of two-class and one-class approaches. A number of one-class and two-class classification techniques have been considered: Linear discriminants, 1-Nearest Neighbour, Mixture of Gaussians, Parzen Windows and the Support Vector Machines. Better results have been achieved using the one-class methods. The dataset has been extracted from a set of SAR images acquired by an airborne X band SAR system mounted on board of a Laerjet 35A, during the Galitia Mission in January-February 2003 (TELAER Consortium), after the sinking of the Prestige oil tanker.

1 INTRODUCTION
Oil spill detection by means of SAR images is possible because of the damping effect of the short wind waves caused by the presence of oil on the sea surface [1-2]. As a consequence, an oil spill is physically a dark patch in SAR images [1-2]. The sea radar image is a representation of the backscatter return, and the intensity of the pixel is proportional to the surface roughness at the scale of radar wavelength (Bragg scattering) [3]. The radar backscatter coefficient is a function of the viewing geometry of the SAR [3]. The backscatter coefficient decreases with the increase of the incidence angle, and the scattering properties of a material depend on the polarization of the incoming radar signal [3]. The contrast between an oil spill and its surroundings depends on a number of parameters as the height of the waves, the amount of oil that has been released, the speed of the wind, etc [1-2]. The shape of the oil spill depends on a number of factors as whether the oil was released from a stationary object or from a moving ship, the amount of oil involved, the speed of the wind, and the current history in the time interval between the oil release and the acquisition of the image [4].
Unfortunately, several natural and atmospheric phenomena produce dark areas in SAR images similar to oil spills. These dark areas are usually referred to as look-alikes, whose presence makes the detection of oil spills a challenging task [1-2].
Oil spills may include all oil-related surface films caused by oil spills from oilrigs, leaking pipelines, passing vessels, while look-alikes include natural films, grease ice, threshold wind speed areas (<3 m/s), rain cells, etc. Oil spills are only man-made slicks due to crude petroleum and its products [1-2].
It is easy to see that oil spill detection over SAR images not only requires the detection of dark patches in the image, but also requires post-processing techniques aimed at discriminating oil spills from look-alikes. Oil spill detection is thus usually framed into three fundamental phases: *dark patch detection*, *features extraction*, and *oil spill/look-alike classification* [1-10]. Features to discriminate among oil spills and look-alikes are typically based on geometrical properties, as well as on radiometric measures and textures.

1.1 Segmentation techniques
As oil spills are characterised by low backscattering levels, the use of thresholding techniques has been investigated for dark spot segmentation. In [5] an adaptive algorithm with the threshold set k dB below the mean value, estimated in an image moving window, is applied. Image thresholding is then combined with a multiscale pyramid approach and a clustering step to better separate the oil spill from its surroundings. In [6] the areas of low backscatter are located automatically, without the intervention of a human operator. This procedure masks the land areas, and selects the dark regions with a normalized radar cross section (NRCS) smaller than one half of the average NRCS computed for the sea area in the image. It then rejects the selected areas that are too small or too large. The small regions are rejected because these slicks are not significant from the coast guard point of view, and the large ones because these are most likely areas with no wind. In [7] a dedicated oil spill processing and analysis tool based on edge detection is applied. Once defined the region of interest by the user, the tool analyzes the overall backscattering of the region and produces a histogram.

Typically, histograms in presence of a dark region contain two peaks; the lower peak is located around the mean backscattering value of the dark object, while the taller is located around the mean value of the background. The local minimum value between the two peaks is used for the segmentation of the image. To this purpose, the darkest pixel in the region is selected as the starting point for the region growing segmentation algorithm. The region grows until the neighbouring pixels have a value grater than the threshold value given by the local minimum previously calculated. This method allows defining the border around the dark region.

TABLE 1 – Features considered in automatic oil spill detection procedures. (adapted from [1])

Features	Del Frate et al., 2000	Fiscella et al., 2000	Topouzelis et al., 2002	Marghany, 2001	Espedal, 1999	Solberg., 1999
Area	■	■	Big Areas		■	■
Perimeter	■	■			■	
Perimeter to Area Ratio		■				
Normalized Perimeter to Area Ratio		■	Shape Index			
Slick Width						■
Length to Width Ratio			■			
Complexity	■	Form Factor	Asymmetry			First Invariant Planar Moment
Spreading	■					
Object Standard Deviation	■	■				
Background Standard Deviation	■	■				
Contrast	■			■	■	■
Gradient	■	■			■	■
Gradient Standard Deviation	■					
Slick Radar Backscattering		■	■		■	
Outside Slick Radar Backscattering		■				
Intensity Ratio		■				
Standard Deviation Ratio		■				
Intensity Standard Deviation Ratio Inside		■				
Intensity Standard Deviation Ratio Outside		■				
ISRI to ISRO Ratio		■				
Mean Difference to Neighbours			■			
Power to Mean Ratio			■			
Close to Big Areas			■			
Close to Land			■			
Close to Fractal Object			■			
Layer Value Texture Based on Sub-objects			■			
Shape Texture Based on Sub-objects			■		Texture	
Distance to a Point Surce						■
Number of Detected Spot in the Scene						■
Number of Neighboring Spots						■
Homogeneity				■		■
Entropy				■		
Energy				■		
Correlation				■		

1.2 Slick feature extraction

After extracting the thresholded dark spot area from the image, a number of features can be computed for each dark spot. Table 1 summarizes the different features adopted by different authors. The individual features are typically subdivided into the following classes:

Geometry and shape of segmented region: geometry and shape features are applied by all methods proposed in literature (Table 1). If the oil slick is a fresh oil spill released from a moving ship (a tanker cleaning its tank), an important feature is the *elongatedness*, which can be expressed as a ratio between the width and length of the slick. Among the shape features, the perimeter and the area of the object are also considered.

Backscatter level of the spot and its surrounding: in [7] it has been shown that the features related to the gradient of the backscattering value from background to slick provided the most valuable information when classification by means of neural networks was used. Due to the heavy effect of wind speed, the *background standard deviation* was also shown to be an important discriminant parameter. Similarly in [6] it has been shown that features related to the background area surrounding the slick were also important.

Spot contextual features: spot contextual features depends on weather conditions at the moment of image acquisition, as the speed of the wind, and also on the distance from possible oil spill source as ships or oilrigs. In [4] the distance to bright spot (ships on SAR images) and to pollution source (i.e. oil platforms) is used. In [5] improved classification results are attained by classifying dark spots in the context of their surrounding and weather information.

Texture: if the pixel intensity is compared to the backscattered signal, textures provide information about the spatial correlation among neighbouring pixels. In [11] features based on grey level co-occurrence matrixes (GLCM) are used. Power-to-mean ratio of the slick and surroundings is used in [5] as a measure of homogeneity.

1.3 Classification methods

As a number of phenomena can generate dark patches in SAR images, the purpose of a classifier is to distinguish oil spills from other cases (look-alikes).

In [6] a Mahalanobis classifier in applied to estimate the probability *p* of a dark spot being an oil spill. The 82% of the oil spill in the test set were correctly classified by this classifier. This result was compared with a compound probability classifier, where the 91% of the oil spills in the test set were correctly classified. A training set of 80 oil spills and 43 look-alikes and a test set of 11 oil spills, 4 uncertain and 6 look-alike were used.

In [5] the probability was estimated by a multivariate Gaussian density function. The algorithm was combined with a prior model for the number of look-alikes, a model for the presence of slick near a bright object and a rule-based modification of the probability density function to take into account feature combinations indicating particular scene conditions. The leave-one-out method with 84 scenes gave a correct classification of 94% for oil spills.

An approach based on multilayer perceptron (MLP) neural network with two hidden layer, was proposed in [7]. The net was trained using the back-propagation algorithm to minimize the error function, and tested on ERS images. Using the leave-one-out method with 139 oil spills, the 82% of oil spills were correctly classified.

The above automatic methods for oil spill detection, exhibit a percentage of correct classification of oil spills ranging from 82% to 94%. These results are related to different data sets, different segmentation approaches to detect dark patches, and different feature extraction processes. On the other hand, all the studies reported in the literature are based on a classical two-class classification methodology, where examples of the two classes, i.e. oil-spills and look-alikes, must be provided to train the classification model.

The main contribution of this study is twofold: i) classical features have been examined/evaluated and ranked in function of their effectiveness; ii) the classification of dark patches has been performed using two-class approaches as well as one-class approaches [12-13]. One-class approaches aim to model the class for which reliable examples can be provided, e.g. the oil-spill class. As a consequence, a dark patch is classified as an oil spill if it fits the model, otherwise it is classified as a look-alike.

2 FEATURE EXTRAXTION AND EVALUATION

The adopted segmentation process is a bottom up region-merging technique starting with one-pixel objects. In subsequent steps, smaller image objects are merged into bigger ones. Throughout this pair-wise clustering process, the underlying optimization procedure minimizes the heterogeneity of the resulting image objects. In each step, a pair of adjacent image objects is merged, so that the heterogeneity level of the new object is below a fixed heterogeneity threshold. The process stops if the heterogeneity level of the merged regions exceeds the heterogeneity threshold defined by the human operator. The human operator can either accept the result suggested by the automatic procedure or reject it and produce a new segmented image, by changing the threshold manually.

Once the border of the dark object is accepted, a number of morphological and physical features regarding the dark object and its surrounding areas are computed (Table 1).

All these classical features have been examined/evaluated and ranked in function of their discrimination capability between oil spills and look-alikes. Four features selection algorithms have been used, namely the *Forward method,* the *Backward method,* the *Branch & Bound method* and the *Individual method*. For each feature selection method, four different distance criterion have been employed, i.e. the *Euclidean distance*, the *Mahalanobis distance*, the *Nearest Neighbour distance* and the *Inter-Intra distance*. Each combination of feature selection methods and distance criterion produced different subsets of "good" features. In order to combine such different results, four "frequency plots" are obtained by counting the times that each feature is ranked in the first five, ten, fifteen and twenty, respectively. These frequencies allowed producing a cumulative ranking that has been used to finally assess the discrimination capability of each feature (see Table 2).

TABLE 2 – Best features set after features discrimination capability evaluation.

(1) - Mean Contrast (μ_{sce} - μ_{obj})	(6) - Intensity Ratio $\left(\mu_{obj}/\mu_{sce}\right)$
(2) - Outside Slick Standard Deviation (σ_{sce})	(7) - ISRO $\left(\mu_{sce}/\sigma_{sce}\right)$
(3) - (GLCM) Contrast	(8) - (GLCM) Dissimilarity
	(9) - (GLCM) Entropy
(4) - Inside Slick Radar Backscattering (μ_{obj})	(10) - (GLCM) Correlation
(5) - Outside Slick Radar Backscattering (μ_{sce})	(11) - Intensity St. Dev. Ratio $\left(\sigma_{obj}/\sigma_{sce}\right)$

3 CLASSIFICATION TECHNIQUES

A classification problem can be formulated in terms of a one-class classification if one of the classes has to be distinguished form all other classes. Typically, in a one-class classification problem two classes are considered: the *target class* and the *outlier class* [12-13].

The *target class* is assumed to be well sampled, in the sense that either a large number of training examples are available for this class, or this class can be more easily modelled. On the other hand, the *Outlier class* can be sampled very sparsely, or examples can be totally absent. For example, examples of outliers may be very hard to collect, or its features might be very expensive to measure, etc..

In our case, the oil spills are considered as the target class, as their characteristics have been thoroughly studied and they can be easily reproduced in laboratory simulations. On the other hand, look-alikes (biogenic class) form the "outlier class", as they can be produced by a large variety of different natural phenomena. It is worth noting that tipically different oil-spills will appear clustered in the features space because they are all generated from the same man-made phenomena. On the other hand, look-alikes are considered the outlier class, as they can be produced by several and very different natural phenomena, so that they are sparsely distributed in the feature space. This fact can be motivated by observing that the values of features associated to different natural phenomena can be very different from the values of the same feature associated to other natural phenomena.

This means that only examples of the target class (oil spill) can be used for classification, while data from outlier objects (look-alikes) could not provide useful information. As a consequence, one-class models estimates the boundary of the area in the feature space containing the target class, i.e. the oil spill class. Therefore, one-class methods are developed from mathematical models based only on examples from the target class, so that the large number of target objects are accepted, while the chance of accepting outlier objects is minimised.

4 EXPERIMENTAL RESULTS

The training dataset has been extracted from a set of SAR images acquired by an airborne X band SAR system mounted on board of a Laerjet 35A, during the Galitia Mission in January-February 2003 (TELAER Consortium), after the sinking of the Prestige oil tanker.

In order to compare the performances of two-class classifiers and one-class classifiers, several experiments have been carried out by varying the number of training objects and the number of features. A number of one-class and two-class classification techniques have been used: *Linear discriminants*, *1-Nearest Neighbour*, *Mixture of Gaussians*, *Parzen Windows* and the *Support Vector Machines* [12-13].

Preliminary results show that the best classification performance is always achieved by one-class classification techniques. In particular, once fixed at 2% the maximum acceptable oil-spill misclassification error (number of oil-spills classified as look alike), the error rate on the look-alike class was evaluated (this error represents the percentage of look-alikes classified as oil-spills). One-class classifiers allowed attaining an error of 1%, whereas two-class classifiers attained an error of 3% (see Figs. 1-2).

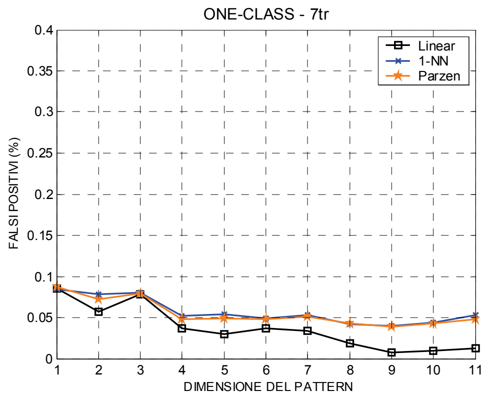

Fig. 1 – Plot of the look-alike classification mean error, once that a 2% oil-spill classification max error has been fixed, for three different type of one-class methods.

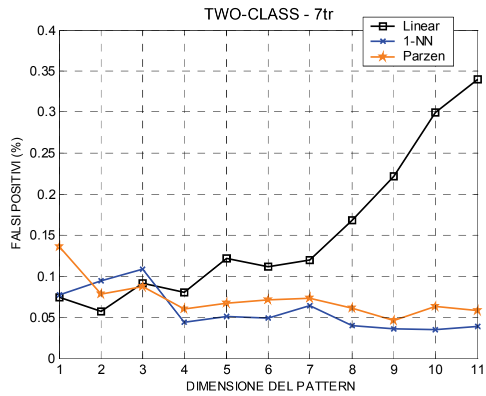

Fig. 2 – Plot of the look-alike classification mean error, once that a 2% oil-spill classification max error has been fixed, for three different type of two-class methods.

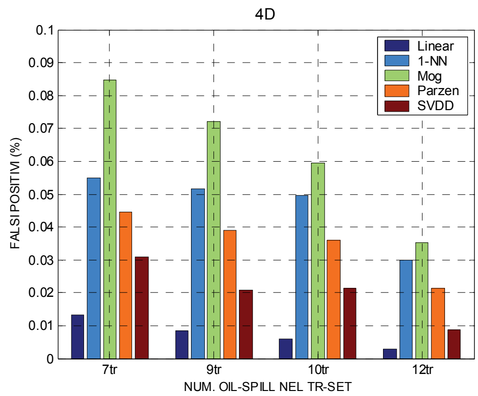

Fig. 3 – Mean error plots of the considered one-class classification methods for different training set dimensions (7tr, 9tr, 10tr, 12tr) and making use of 4 characteristics (4D).

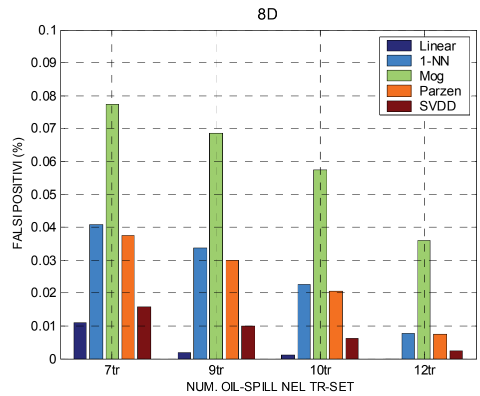

Fig. 4 – Mean error plots of the considered one-class classification methods for different training set dimensions (7tr, 9tr, 10tr, 12tr) and making use of 8 characteristics (8D).

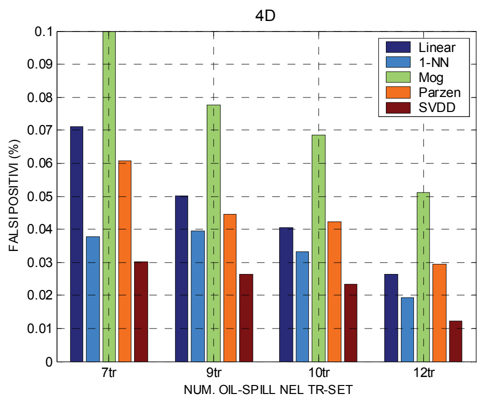

Fig. 5 – Mean error plots of the considered two-class classification methods for different training set dimensions (7tr, 9tr, 10tr, 12tr) and making use of 4 characteristics (4D).

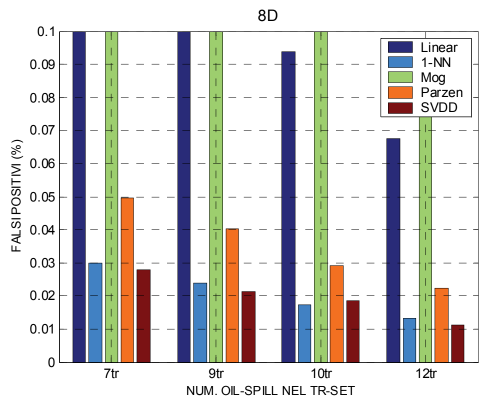

Fig. 6 – Mean error plots of the considered two-class classification methods for different training set dimensions (7tr, 9tr, 10tr, 12tr) and making use of 8 characteristics (8D).

As far as the feature selection process is concerned, all the features typically used in the literature have been ranked according to their effectiveness. Results show that the highest accuracies can be attained by using either the first four or the first eight features (see Figs. 3-6) obtained by the features selection phase (see Table 2). These features include the mean contrast between the background and the dark patch, the outside dark patch standard deviation (as the dark patch in the image depends also on the wind speed), the (GLCM) contrast, the inside slick dark patch radar backscattering, the outside slick dark patch radar backscattering, the intensity ratio, the ISRO and the (GLCM) dissimilarity. The best classification performance, for any training set and pattern dimensions, has been achieved with the *Linear discriminants* one–class type method. The second best classification result has been achieved with the *Support Vector* one–class type method. This latter technique has been the best two–class method.

5 CONCLUSIONS

In this study, one-class and two-class classification methods have been explored to classify dark patches in marine SAR images, i.e. the capability to distinguish among oil-spill and look-alike has been explored. In particular, the study has been focused on two aspects:

i) analysis of the classical features used in the oil-spill classification procedures, and their ranking in function of their effectiveness;

ii) classification of dark patches using a two-class approach as well as a one-class approach.

The features which have shown the best discrimination capability between the oil-spill and the look-alike classes are principally related to the variations of the contrast in correspondence of the transition from free sea surrounding area and dark patch, i.e. the *Mean Contrast* feature and the *Contrast* (*GLMC*) feature. Another feature which has shown a good discrimination capability is the *Outside Slick Standard Deviation* since its strong dependence the wind. It is important to keep in mind that the features have a good discrimination capability in the features space only if they are jointly considered

Once that the best features have been selected, a set of one-class and two-class classification techniques have been tested for different dimensions of the training set: *Linear discriminants*, *1-Nearest Neighbour*, *Mixture of Gaussians*, *Parzen Windows* and the *Support Vector Machines*. The best classification performance has been achieved with the *Linear discriminants* one –class type method.

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