Pattern oil spills characterization in optical satellite images

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INTRODUCTION:

Oil spills are causing serious damage to marine and coastal ecosystem. The detection of oil spills can be efficiently improved by the use of satellite images since they offer an economical and easy way of large areas monitoring. SAR images have been widely used for oil spill detection, as they are not affected by local weather conditions and cloudiness. Anyway, radar backscatter values for oil spills are similar to backscatter values for very calm sea areas because the presence of an oil spill dampens capillary and short gravity waves. This causes a high number of false alarms.

Oil spills detection using optical images is more difficult because good weather conditions and day light are needed. However these weather conditions are likely for instance in the Mediterranean area and the high rate of optical sensor images availability make this approach worth of interest.

Up to date the scientific literature is poor of contribution in this field. The aim of this work is to study the possible advantages of an optical investigation.

SYSTEM SCHEME:

Oil spill detection can be seen as a classification problem where two classes are identified: oil spills, which are produced by oil pollution and look-alikes, which are related to natural phenomena. Here is a scheme of the classification system:

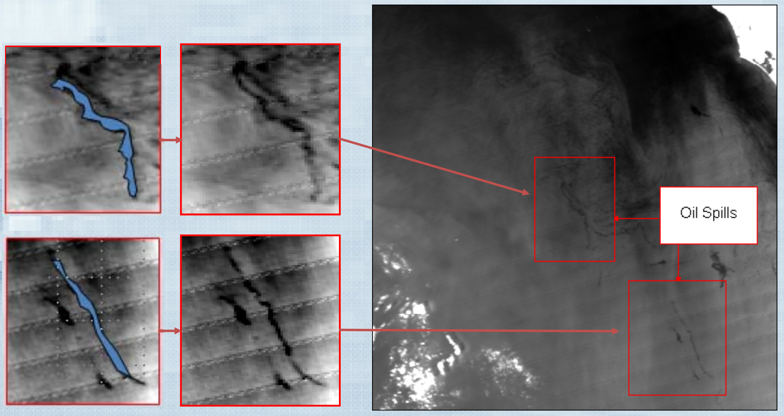
Multi-spectral satellite image (MODIS/MERIS) → **Contrast enhancement** → **ROI segmentation** → **Features extraction** → **Classification**

ROI SEGMENTATION:

The original satellite image is contrast enhanced through a local histogram equalization performed on two bands ratio:
MODIS: band 1 (620 nm-670 nm)/band 2 (841 nm-876 nm)
MERIS : band 7 (660 nm-670 nm)/band 13 (855 nm-875 nm)

Candidate oil spill regions are identified by segmentation carried out using the Isodata algorithm with the following parameters:
Maximum number of classes = 5;
Minimum number of classes = 2;
Number of iterations = 100;
Minimum number of pixel for each class = 20

On the right there are some oil spill examples together with the original image.



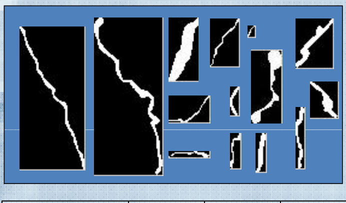
FEATURES EXTRACTION:

In order to discriminate between oil spills and look-alikes, the examples are described using a number of physical and geometrical features characterizing the object.

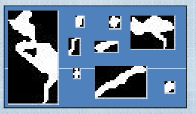
Among the features the most effective one seems to be the *spreading (S)*, computed performing a principal component analysis on the vector whose components are the coordinates of the pixels belonging to the object. In particular, if λ_1 and λ_2 are the two eigenvalues associated to the covariance matrix ($\lambda_1 > \lambda_2$), the spreading is given by the following expression:

$$S = \frac{100\,\lambda_2}{\lambda_1 + \lambda_2}$$

This feature assumes low values for long and thin objects and high values for objects close to a circular shape.



Training set: some oil spill examples



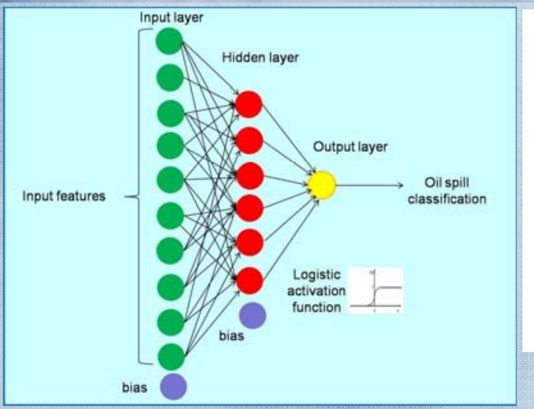
Training set: some look-alike examples

Features	Min	Max	Mean	St. Dev.
Area	0.6875	32.5625	11.58482	10.4894
Perimeter	5.035534	85.92641	30.07578	22.51498
Complexity	1.631798	4.549723	2.621107	0.89985
St. Dev. b1	0.000961	0.002988	0.001785	0.000699
St. Dev. b2	0.001398	0.003647	0.002241	0.000804
Mean Contrast b1	0.000359	0.009438	0.004183	0.002518
Mean Contrast b2	0.000966	0.011573	0.005254	0.003001
Max Contrast b1	0.003261	0.015453	0.007836	0.003497
Max Contrast b2	0.005099	0.018665	0.009659	0.003999
Spreading	0.292578	5.401991	2.562118	1.717383

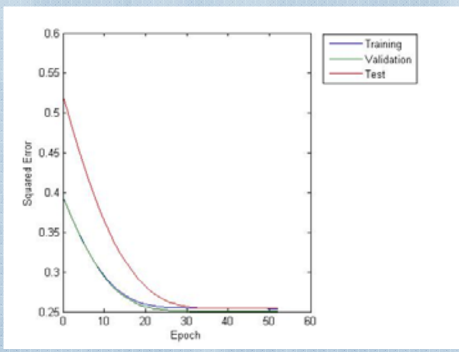
Features	Min	Max	Mean	St. Dev.
Area	0.875	41.75	9.201389	13.48005
Perimeter	3.62132	46.27386	13.96275	14.34967
Complexity	0.951032	2.020238	1.36226	0.400046
St. Dev. b1	0.000431	0.003078	0.001312	0.000822
St. Dev. b2	0.000488	0.003753	0.001614	0.000991
Mean Contrast b1	0.001403	0.015988	0.004254	0.004572
Mean Contrast b2	0.001676	0.01968	0.005328	0.005612
Max Contrast b1	0.00207	0.022015	0.00656	0.006156
Max Contrast b2	0.002508	0.027118	0.00815	0.007548
Spreading	1.920247	42.92462	18.87223	13.77393

NEURAL NETWORK CLASSIFICATION:

The classification is performed by an artificial neural network, which can be considered as a mathematical model composed by many non linear computational elements, the neurons, operating in parallel and massively connected by links characterized by different weights. The input for the network consists of the set of calculated features providing information about the object, while the output is the probability of real oil spill. A feed-forward Multilayer Perceptron neural network is used. The network is composed by 10 input neurons, an hidden layer composed by 6 neurons, and an output neuron. Each hidden neuron computes a function of the weighted sum of its inputs, using a logistic activation function.



Network architecture



Global squared error of the net computed on the training, validation and test sets

CONCLUSIONS:

An oil spill classification algorithm has been realized using an artificial neural network. A set of characterizing features has been identified in order to describe the oil spills candidates. The net has been trained using a set of oil spill and look-alike examples extracted from the original satellite images. This is a preliminary work, further development has to be carried through. In particular a larger training set is being constructed in order to better train the net, and other network architectures will be studied. Anyway the use of optical images seems to be very promising.

ACKNOWLEDGEMENTS:

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