

A Novel Sinergy Between Remote Sensing and GIS for Oil Spill Detection on Satellite Imagery

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Abstract – The large amount of images available today, thanks to the increasing of the number of orbiting EO satellites (Earth Observation Systems), which are able to provide information of every region of the Earth, represents an indispensable instrument for monitoring any terrestrial ecosystem. EO systems allow to detect and follow fast changing phenomena (like natural and anthropic disasters) providing the needed information for planning the necessary measures and reduce the impact of these events.

This paper aims at showing the results obtained through the transformation of Mathematical Morphology algorithms (which have already shown their effectiveness) in IDL based algorithms (using ENVI EX rule sets) that can provide identical performances. The direct execution of these algorithms in a GIS environment, taking into account topology restrictions, allows to directly generate maps containing potential oil spills isolated on satellite images (exploiting the geometrical and physical characteristics of oil spills) together with contextual information on the same maps (typical of the GIS environment, as the wind regime, presence of vessels, etc) in order to assign a probability to candidate spots and create a much more accurate oil spill detection process.

Keywords: Mathematical Morphology, Oil Spill, SAR Images, Geographic Information Systems.

1. INTRODUCTION

Oils spills in the sea are considered to be a serious environmental problem. Every day illegal discharges from ship and accidents at sea with oil spilling occur. The ITOPF database contains information on about 10,000 oil spills in 1970-2001 from tankers and oil carries. Oil pollution as a serious environmental disaster often leads to significant, long-term impact on the environment, ecology and socio-economic of the polluted area. Fortunately major oil spills are of public concern and usually under control of pollution authorities. On the other hand small oil spills occurring in open sea due to ship operations are usually uncontrolled, unaccounted in oil spill balance and have smaller public concern. In order to implement effective oil spill countermeasures, it is necessary to develop oil spill monitoring systems. Remote sensing, with its capability of detecting spectral characteristics of oil films, has been becoming an important tool to monitor and manage oil spills.

Synthetic Aperture Radar (SAR) images are extensively used for the detection of oil spills in the marine environment, as they are independent from sun light and are not affected by cloudiness. Radar backscatter values from oil spills are very similar to backscatter values from very calm sea areas and other ocean phenomena named “look-alikes” (e.g. currents, eddies, upwelling or down-welling zones, fronts and rain cells). The basic methodology to the oil spill detection by SAR satellite remote sensing can be summarized in four steps (Brekke &

Solberg, 2005). First, all dark signatures present in the image are isolated. Second, features for each dark signature are extracted. Third these features are tested against predefined values. Finally, probabilities for each candidate signature are computed to determine whether it is an oil spill or a look-alike phenomenon.

Geographic information systems (GIS) can significantly contribute to correct the interpretation of the slick signatures visible on synthetic aperture radar (SAR) images. GIS approach to a problem of oil spill mapping includes integration of the geographical, remote sensing, oil infrastructure data and slick signatures, detected by SAR (Ivanov, 2008). An integral study from different sources (ie. spatial databases, ship routes, oil production infrastructure, winds) in several cases, gives the key to understand the slick dynamics and context. Remote sensing and GIS tools working together help decision makers to take advantages from both technologies in order to make reliable oil spills maps. SAR images and extracted oil spill signatures integrated into GIS significantly improve possibilities of oil spill monitoring system (Figure 1). Moreover, the GIS, as shown below, can considered as a core of the oil spill monitoring system allowing integration of all available data and information and dissemination of the final product - oil spill distribution maps to end users/decision makers (Ivanov, 2008).

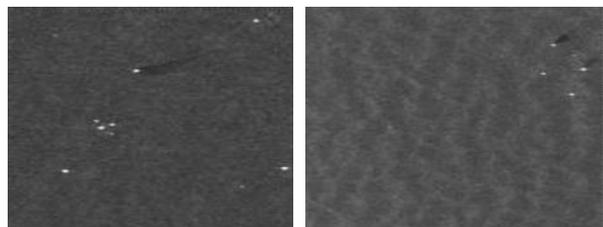


Figure 1. ENVISAT ASAR WSM. Norway Sea - Individual platforms are visible as bright white spots.

Possible oil spill is probably associated to North Cormorant platform (left). Small discharges of oil are visible near the platforms Ninian Northern and Ninian Central (right). © ESA 2007.

Several algorithm aiming at detecting oil spill by using SAR images have been implemented (Del Frate et al., 2000; Solberg et al., 1999). Most of them rely on the detection of dark areas. Any formation on the image that 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 presents three main difficulties if semi-automated or automated methods are used. First, fresh oil spills are brighter than older spills. They have a weak backscattering contrast relative to their surroundings, therefore they cannot be easily discriminated. Second, areas surrounding dark zones can have various contrast values, depending on the local sea state, oil spill type and image resolution. Third, other phenomena can produce dark areas too, such as organic film, grease, ice, wind-front areas, areas sheltered by land, rain cells, current shear

zones, internal waves and upwelling zones. Therefore, classification of the dark areas as oil spills and look-alikes is required.

The basic idea of this study is to extract, in automatic way, the dark spots present on SAR images exploiting not only the spectral but also the morphological characteristics of the objects of interest, in order to simplify the images analysis by the users. Starting from a rule-set created in Matlab environment by using Mathematical Morphology (Santilli & Laneve, 2010), the authors have transferred this rule-set and knowledge to the Envi Ex environment and then to the GIS environment, in order to include in the feature extraction process the contextual information too. The latter are able to assign a greater degree of confidence to the potential spots extracted. The GIS environment is probably the most adaptable and versatile to the manipulation and processing of contextual information, thereby making the whole process of extraction here presented more robust and reliable (figure 2).

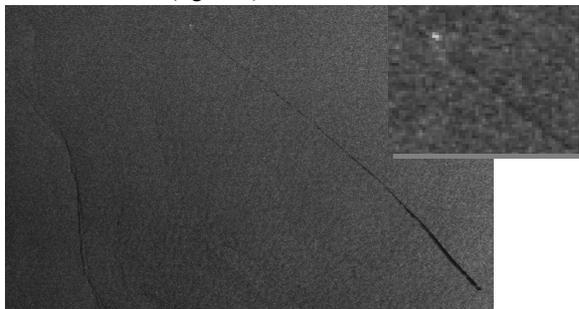


Figure 2. ENVIASAT ASAR WSM. Mediterranean Sea. Ship is clearly visible as bright white spot. While two slicks were detected the right one is correlated with a ship.

2. DATA AND METHODOLOGY

The automatic procedure (figure 3) to obtain the map with relevant slicks, first masks the land present in the image of the area of interest. Second, the resulting image is filtered to facilitate the segmentation process, and dark regions are identified with a feature extraction rule sets algorithm. The features identified are converted to a geographic information system format (shape format) in order to relate them into an entire environment. And finally slicks are categorized by a significance level (Marzialetti, 2010).

3.1. Pre-processing phase

This phase includes the following steps:

3.1.1. Masking-Clipping

In order to eliminate from the image everything that it's not related with the region of interest, the original image is clipped by using a vector file.

3.1.2. Filtering

As it was shown by Karathanassi (Karathanassi, 2006) the segmentation yields better results if more than one layer is used. So, in order to achieve an optimal image to which apply the selected rule sets, a three layer image was stacked. First layer corresponds to the original, the second one to a mean 3x3 filter, and the last layer has been obtained by using a Lee 5x5 and a Local 7x7 filter in sequence.

3.1.3. Feature Extraction rule set application

ENVI-Ex has several predefined spatial, textural and spectral attributes, that can be manipulated adjusting in a friendly environment parameters that were previously extracted from the analysis developed by using the Matlab algorithms. Some of these are related with length of identified features, convexity, solidity, roundness, form factor, rectangle fit, the angle subtended by the major axis of the polygon and the x-axis in degrees, roundness, number of holes or holes ratio among others.

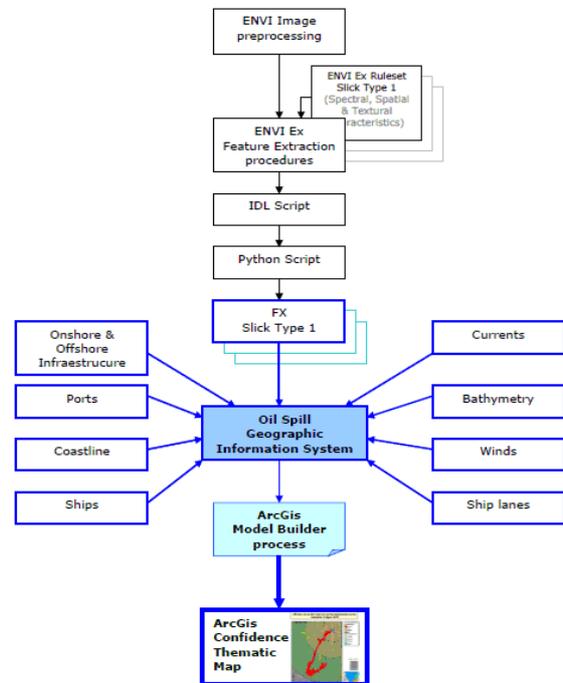


Figure 3. Workflow of automatic oil spill system approach.

Variations on shapes characteristics taken from Russ (2003) and incorporated in rules sets proceedings are:

1. COMPACTNESS: a shape measure that indicates the compactness of the polygon. A circle is the most compact shape with a value of $1/\pi$. The compactness value of a square is $1/2(\sqrt{\pi})$. $COMPACT = \sqrt{4 * AREA / \pi} / \text{outer contour length}$.
2. AREA: total area of the polygon, minus the area of the holes. Values are in map units.
3. MAJAXISLEN: the length of the major axis of an oriented bounding box enclosing the polygon. Values are map units of the pixel size.
4. MINAXISLEN: the length of the minor axis of an oriented bounding box enclosing the polygon. Values are map units of the pixel size.
5. HOLESOLRAT: the ratio of the total area of the polygon to the area of the outer contour of the polygon. The hole solid ratio value for a polygon with no holes is 1.0. $HOLESOLRAT = AREA / \text{outer contour area}$.
6. ELONGATION: a shape measure that indicates the ratio of the major axis of the polygon to the minor axis of the polygon. The major and minor axes are derived from an oriented bounding box containing the polygon. The elongation value for a square is 1.0, and the value for a rectangle is greater than 1.0.
7. $ELONGATION = MAXAXISLEN / MINAXISLEN$
8. FORMFACTOR: a shape measure that compares the area of the polygon to the square of the total perimeter. The form factor value of a circle is 1, and the value of a square is $\pi/4$.

9. FORMFACTOR = $4 * \pi * (\text{AREA}) / (\text{total perimeter})$ (formfactor varies with surface irregularities, but not with overall elongation).
10. PIXEL VALUES STATISTICS: minimum, maximum, average and standard deviation values of the pixels comprising the region.
11. INTENSITY: intensity often provides a better measure of brightness than using the AVGBAND_x spectral attribute.

3.1.4. Features Weighed in a Geographical Environment.

To fulfil the objective of automatically detecting oil spills and distinguishing at the same time them from look-alikes, geographic information systems became the most appropriate environment. After the necessary image pre-processing, taking into account specially the calibration complexity, the GIS is enriched with features from different sources, weighting every extracted feature, and cataloguing them in order to achieve the confidence map.

4. RESULTS

The core system of this study is the automatic dark spots extraction from the SAR scenarios by rule-set application in ENVI-Ex environment. This software has several predefined spatial, textural and spectral attributes, that can be manipulated adjusting in a friendly environment parameters that were previously extracted from the several algorithms developed in Matlab.

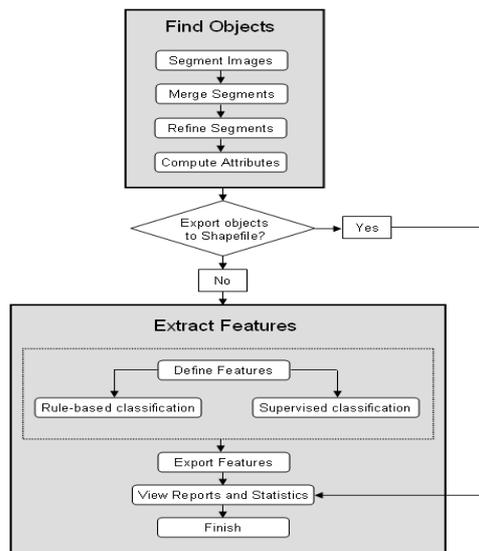


Figure 4. Workflow used in this study to extract dark spots by Envi Ex.

The ENVI-Ex methodology applied to our cases can be summarized as follows:

1. Scale definition: set an initial value for the segmentation Scale Level;
2. Merge threshold: merging is an optional step used to aggregate small segments within larger, textured areas such as slicks in this case, where over-segmentation may be a problem. The Merge Level parameter represents the threshold lambda value, which ranges from 0.0 to 100.0.
3. Feature extraction workflow: the workflow (figure 4) consists of two primary steps: Find Objects and Extract Features. The Find Objects task is divided into four steps: Segment, Merge, Refine, and Compute

Attributes. When you complete this task, you will perform the Extract Features task, which consists of supervised or rule-based classification and exporting of results to shapefiles and/ or raster images (© ENVI Ex Help).

In particular, the methodology above-described was applied on several ENVISAT/ASAR and RADARSAT images, which provides a reasonable degree of spatial resolution and, as it says in the product handbook, contributes to monitoring natural and man-made pollution over the ocean providing continuous and reliable data sets for applications such as coastal protection, pollution monitoring and ship traffic monitoring.

4.1. Working of ENVI Ex methodology.

The figure 5 shows the results obtained by applying the whole automatic ENVI Ex feature extraction procedure to a couple of SAR images (one ENVISAT/ASAR and one RADARSAT 1).

4.2. Slick and ship detection from SAR image.

Synthetically, the process, as it is showed in figure 6, begins with the image pre-processing aiming at a significant speckle reduction, and at creating an image composition that simplifies the segmentation.

Once the segmentation is obtained, a set of rules related to oil spills and look-alikes spectral, textural and spatial characteristics is applied reaching a GIS format dataset. In this environment, the features extracted are related each other and weighted, reaching the necessary components to make confidence maps.

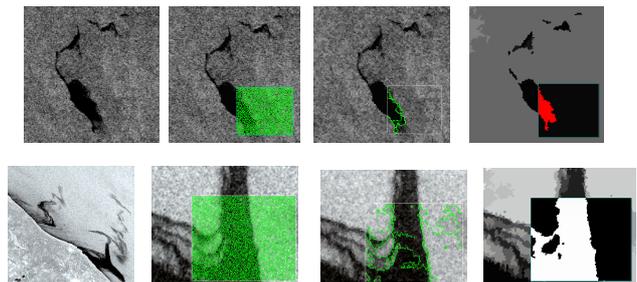


Figure 5. Whole ENVI Ex methodology applied on ENVISAT ASAR WSM image on Mediterranean sea (© ESA 2011, top) and on RADARSAT image (bottom) on River Plate – Argentina (© CONAE, 1999).

4.3. Slick exclusion identified as look-alike

Wind levels influence the backscatter response and then the visibility of slicks on the sea surface. Relatively to this topic, some studies (Gade et al. 2000, studies over the Baltic, North & Mediterranean sea) found that with high wind speed (>10m/s) few oil spills were detected with SAR images, between 3 and 10 oil slicks are visible with a quite homogeneous background. Below 3m/s wind speeds show that exist a high probability of oil slick look-alikes, and near 0m/s there is not a backscattering response from the sea surface.

Solberg et al. (1999) set this contextual factor manually by inspecting the image visually. Other possibilities are to incorporate wind information obtained from external sources. Further, the automatic estimate of wind speeds is possible by applying an inverted CMOD4 model (Salvatori et al., 2003). Some authors (Brekke et al., 2005) conclude that wind vector results useful in knowing the evolution of the spill and for obtaining correct classifications.

Nest Wind Field Estimation operator is a tool able to retrieves wind speed and direction on C- SAR imagery. In particular,

wind speed is estimated by using CMOD5 model for Normalized Radar Cross Section (NRCS) developed for VV-polarized C-band scatterometry

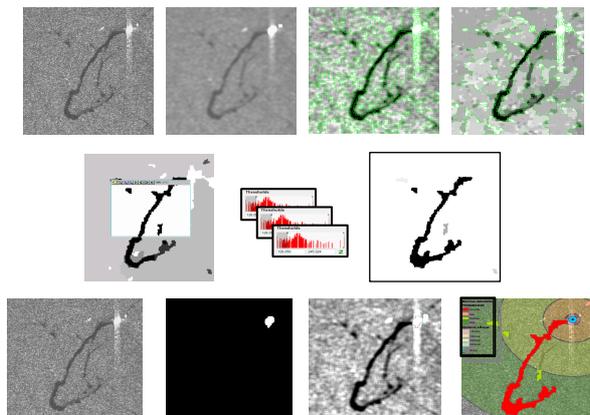


Figure 6. Sequence of steps needed to extract the oil slick from the original SAR image (top and middle) by using ENVI Ex and exporting its results in GIS environment for using contextual information (bottom).

This procedure was applied to an ENVISAT/ASAR VV polarized image on the Mediterranean sea. We can see near to the centre region of the image a real oil spill ship-related. Meanwhile the bottom zone was detected as probably oil spill due to its textural and spectral characteristics, the wind factor allows us to exclude it. In this case, the Wind Speed Estimator achieves a clear separability between a real oil spill vs a typical look-alike (figure 7).

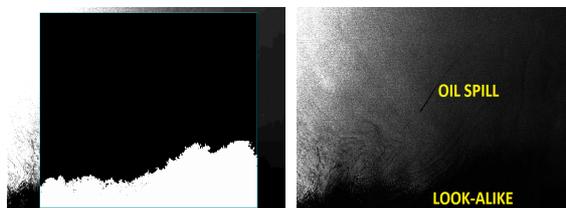


Figure 7. Envisat/ASAR, 17 Aug. 2010. © ESA 2010. We can see (left image) an extracted feature obtained from a wind field layer provided by Nest Wind Field Estimation operator, which give us a clear class separability between real oil spill and a look alike caused by low wind speed.

5. CONCLUSIONS

Nowadays, several methodologies proposes manual, automatic or semi-automatic OSD procedures and feature extraction techniques are implemented over different platforms. Despite of this, the combination with contextual databases, infrastructure, related with an integral slick analysis (ship-slick, platform-slick, wind speeds, etc) seems to be a solution to understand distribution of oil spills in the marine environment and introduce a primary exclusion of real oil slicks from look-alikes.

In this context and in order to understand situations that are not identified in automatic or semi-automatic steps, this methodology creates the necessary value-added data expected by decision makers.

Further studies will be carried out by employing shape descriptors, detailed (Russ, 2003) among others, in other platforms - such as R -, evaluating robustness of features

combination (Topouzelis 2009), maximizing the discrimination of oil spills and look-alikes phenomena.

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