CLASSIFICATION OF OIL SPILLS AND METEO OCEANOGRAPHIC EVENTS DETECTED IN SAR IMAGES

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KEY WORDS: Synthetic aperture radar, oil spill, ocean features detection, classification, machine learning

ABSTRACT:

An automatic classification procedure was developed to identify different oceanic events, detectable in orbital radar images. The procedure was customized to be used in the southeastern Brazilian coast, since the classification training and test used examples extracted from 402 RADARSAT-1 images acquired in this region. Different sets of spectral, geometric and contextual (meteoceanographic and location) features of selected low backscatter areas were evaluated. Machine learning procedures (neural networks, decision trees and support vector machines) were used to induce classifiers to differentiate between seven classes, belonging to two categories. The classification procedure involves two steps: first the features area classified in one of two categories - oil pollution or meteoceanographic event. In the second step, the identification of tree classes of oil pollution and four classes of meteoceanographic events is done. The oil spill related classes are associated to oil exploration and production, ship releases and others. The meteoceanographic phenomena include biogenic slicks and/or upwellings, algae blooms, low wind areas and rain cells. The models induced by support vector machines and neural networks achieved good results, allowing the operational implementation of the proposed procedures.

1. INTRODUCTION

The increased availability of spaceborne Synthetic Aperture Radar (SAR) is providing opportunities for large scale oceanic monitoring and oil spill detection, compared to scattered ship observations or aircraft surveillance over limited areas. Orbital SARs are able to acquire images with a large swath, independent of weather and illumination conditions. The images generated provide data with sufficient spatial resolution to detect different types of environmental events. The processing and delivery of the images by some systems in almost real time, makes this technology very useful to orient field checks and response action when necessary.

Currently, there are no doubts regarding the capacity of the radar images to detect various events, associated with pollution emissions, in coastal and ocean areas. However, a series of ambiguities, inherent in the image forming process can induce mistaken interpretations. Various meteo-oceanographic phenomena and events associated with the presence of substances that alter the surface tension produce dark patches in the images, similar to those associated to the presence of oil (Clemente-Colón and Yan, 2000). Therefore, the image interpretation process is highly dependent on the interpreter experience as well as the availability of ancillary information.

With the objective of optimizing image analysis various authors have investigated methods to automate the oil spill detection, in SAR (*Synthetic Aperture Radar*) images (Kubat *et al*., 2000; Espedal and Wahl, 1999; Del Frate *et al*., 2000; Solberg *et al*., 1999). As the patches produced by oil could have spectral characteristics similar to the other meteo-oceanographic events, procedures based on the pixel clustering in the spectral space – image thresholds, segmentations – are not effective to discern them. As a result, the majority of automated oil spill detection procedures include the following three principal stages: dark patch detection, feature extraction and classification. Usually the procedures aim the classification of the detected patches into two classes: oil spills or look-alikes.

In this context, this paper presents the results obtained with the development of an object-oriented classification procedure, for the automatic identification of dark patches detectable in SAR images. The procedure is customized to be used in the coastal and oceanic areas of Southeast Brazil. Different sets of features and machine learning inducing algorithms (neural networks, decision trees and support vector machines) were evaluated for the automatic classification.

2. METHODOLOGY

The work evolved in the following stages (Figure 1): a) Examples selection, b) Segmentation of the selected patches, c) Extraction of spatial, spectral and contextual features. d) Classifiers creation and evaluation. The selection of representative examples involved the analysis of 402 RADARSAT-1 images (ScanSAR Narrow A , ScanSAR Narrow B and Extended Low-1) acquired between July 2001 and June 2003, in the Southeast Brazil. The examples identification of was made with the visual interpretation of the images, confirmed by *in situ*, as well as exploration and production facilities location and meteo-oceanographic ancillary data, in a GIS (*Geographic Information System*) environment.

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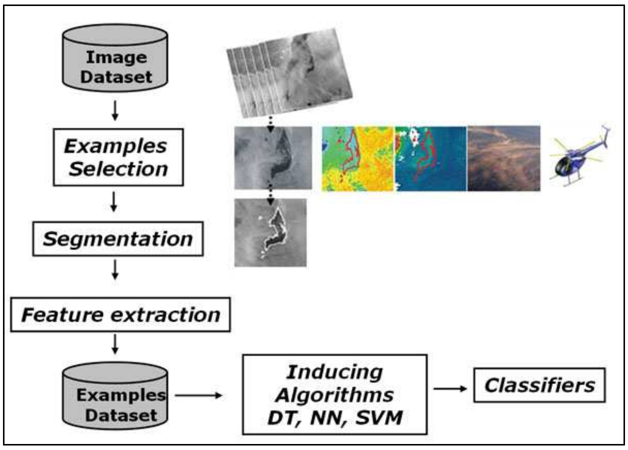

Figure 1. Work stages summary.

The location of exploration and production installations (pipelines, production and drilling rigs and ships, etc.) was used for contextualization. The meteo-oceanographic information included the Sea Surface Temperature (SST) obtained from NOAA (National Oceanic and Atmospheric Administration)/AVHRR (Advanced Very High Resolution Radiometer); chlorophyll a concentration from SeaWiFS (Sea-viewing Wide Field-of-view Sensor) and MODIS (Moderate-resolution Imaging Spectroradiometer); wind field derived from QuikSCAT data (Figure 2).

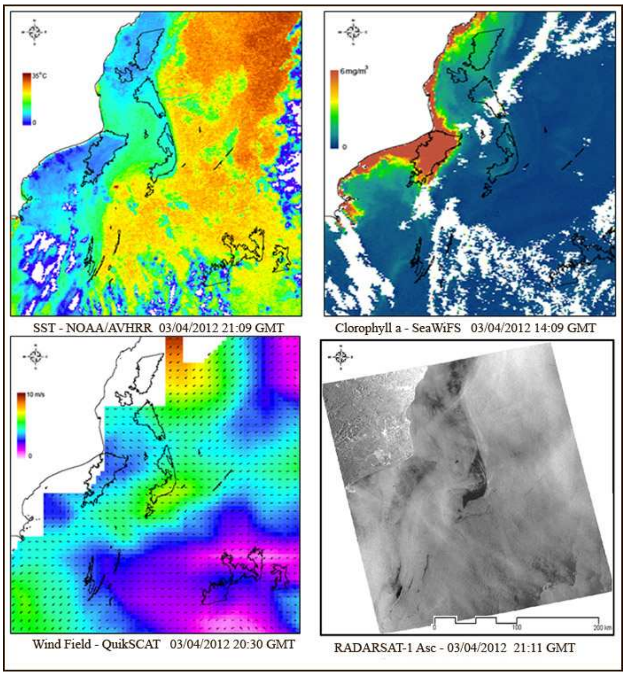

Figure 2. Example of data set used to patches selection and characterization: RADARSAT-1 Asc image (April 3, 2002 – 21:11 GMT), SST –NOAA, chlorophyll a - SeaWiFS and MODIS, wind field - QuikSCAT.

A segmentation procedure (Baatz *et al*., 2003) with multiple resolutions was used to patches individualization (Figure 3). Before the segmentation, the radar images were processed for spatial and radiometric corrections. The spectral features were obtained using non-calibrated image values. This option considered the viability of the future operational use of the classifier, in almost real time. The access to the raw data and calibration process significantly increase the computation time.

Following the segmentation the main features already used in previous published works were calculated, together with riginal ones specific to this area and dataset. Procedures for features calculations were implemented using geographic analysis procedures, modeled in SIG . A total amount of 40 features were calculated, divided according to their representative characteristics as: scene of occurrence (3 features), spectral (4 features), textural (2 features), geometrical (9 features), meteo-oceanographic (10 features), and location (12 features). Details about the features are available in (Bentz, 2006).

In this way, it was possible to individualize and calculate all the features for 779 events examples using the image dataset, which are divided into seven classes, divided into two categories as follows: Category I: Oil Spills (358 examples): E&P Operational spills (214), Ship releases (76) and Orphan Spills (68). Category II: Meteo-oceanographic phenomena (421 examples): Biogenic oils and/or Upwellings (264), Algae Blooms (61), Low wind areas (51) and Rain cells (79). Permanent oil seeps were not identified in the image dataset analyzed. Orphan Spills are those that were identified as petrogenic oil with in situ data but whose spill's causing event was not discovered.

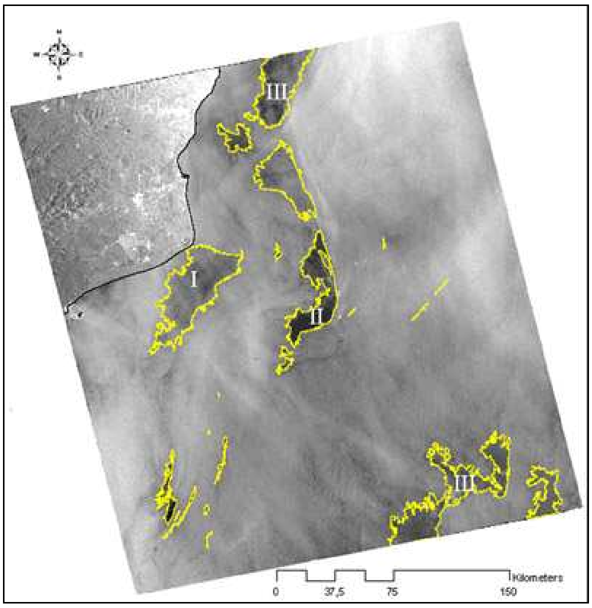

Figure 3. Example SAR image segmentation applied to patch individualization. RADARSAT-1 Asc image (April 3, 2002 – 21:11 GMT).

3. CLASSIFICATION PROCEDURE

The classification consists of the distributing samples described by a fixed set of attributes into one of a finite set of categories or classes. For the classifier construction task, it is necessary to choose a learning strategy, a set of data for training and tests. Several techniques from many different areas of statistics and artificial intelligence have been applied to this problem. In this work, three inducing algorithms were used – Decision Trees (DT), Neural Networks (NN) and Support Vector Machines (SVM).

The definition of the classification strategy involved tests with the objective of evaluating if the classification could be made with a single classifier, to separate the seven existing classes. The test results don't support the adoption of this strategy, because the classifier with the best performance produced inefficient and complex results. Therefore, the strategy adopted was the classification in stages. In the first, the events are classified in accordance with the category (Category I or II) and the second, in accordance with the specific class of each category. In this strategy, three classifiers are necessary to answer the following questions: **1 -** Is the event an oil spill or meteo-oceanographic phenomena? **2 -** If the event is an of oil spill, which class it is? **3 -** If the event is a meteo-oceanographic phenomena, which class it is?

The classifiers performance was also tested, without the use of the meteo-oceanographic contextual data. Problems in the acquisition and availability of this data are frequent, as they are acquired in different platforms and depend on the cloud cover conditions.

It was use 60% of the samples for training, 20% for validation and 20% for test. The test samples were randomly chosen, with stratified *10*-fold crossvalidation. The DTs were obtained with the use of an algorithm adapted from CART® (*Classification and Regression Trees*). To obtain the NN the *Intelligent Problem Solver* (STATISTICA v.7.) was applied. This procedure evaluates different network structures, according to the parameters specified by the user. The classifiers using SVM were created using a Radial Basis Function (RBF) as kernel.

4. RESULTS

There are various measures to estimate classifiers performance described in the literature. The AUC (Area Under ROC Curve) measure were used in this study, generalized for problems with multiple classes using the first strategy proposed by (Espíndola and Ebecken, 2005).

For Question 1 (Oil spill or meteo-oceanographic phenomena?), the best results were obtained with the classifiers induced by SVM, followed by the NN models (Table I). There was little difference in the performance of the SVM and NN (1 to 2%). The NN structure that obtained the best results was the Multilayer Perceptron (MLP). The lack of meteo-oceanographic information decreases the classifier performance by 1 to 2 %.

The SVM classifier also obtained the best results for the identification of oil spill classes (Question 2). The absence of meteo-oceanographic features doesn't produce a significant decrease in the classifier's performance.

The best results for the identification of meteo-oceanographic phenomena (Question 3) were obtained with the SVM induced classifiers. In this case, the absence of the meteo-oceanographic features caused a significant reduction in the model performances.

The Figure 4 presents a summary of the errors obtained using the classifiers. Using the meteo-oceanographic features it was possible to answer Question 1, 2 and 3 with an estimates error of 7%, 16% and 14% respectively. Not using the meteo-oceanographic features the estimated errors were 10%, 19% and 25%.

TABLE I. CLASSIFIERS RESULTS.

	DT	*NN*	*SVM*
Question	**AUC (%)**	**AUC (%)**	**AUC (%)**
Question 1	**84**	**90**	**93**
Question 1 without METOC features	**83**	**89**	**90**
Question 2	**84**	**87**	**91**
Question 2 without METOC features	**82**	**87**	**91**
Question 3	**86**	**82**	**93**
Question 3 without METOC features	**76**	**78**	**85**

AUC: Area Under ROC Curve; DT: Decision Tree; NN: Neural Network; SVM: Support Vector Machine.

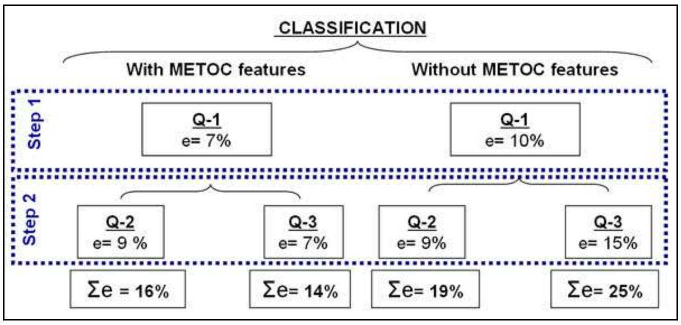

Figure 4. Errors values obtained with the best classifiers (SVM), for the different questions (Q-1, Q-2 and Q-3), with and without the use of meto-oceanographic features. ∑e = Sum of errors.

5. CONCLUSIONS

Classifiers were created able to identify seven types of coastal and oceanic environmental events, detectable in orbital radar images. The process involved two stages: first the events are divided into two categories – Oil spills or Meteo-oceanographic phenomena. In the second stage the events are classified according to the classes specified in each category: <u>Oil Spills Classes:</u> E&P Operational Spills, Ship releases and Orphan Spills. <u>Meteo-oceanographic Classes</u>: Biogenic oil and/or Upwelling, Algae Blooms, Low wind and Rain cells.

Various features were evaluated and the non-availability of contextual meteo-oceanographic data was considered. The models based on SVM using RBF as kernel function presented the best results for all the cases evaluated. The NN (MLP type) also presented good results.

The non use of meteo-oceanographic data caused a reduction in the order of 3% on the performance of the classifier, in the first stage. In the second stage, the absence of meteo-oceanographic features produces a significant decrease in the meteo-oceanographic phenomena identifications, not affecting the performance to identify the three types of oil spill events.

The classifiers could perform better with new training, so long as more examples were available. The uses of bagging, boosting and ensemble methods are other options to increase the performance of the classifying process.

The availability of new satellites, capable of acquiring data in different spectral regions (microwave, visible/near-infrared, thermal infrared) simultaneously, has a large potential to improve the availability and quality of meteo-oceanographic features.

The classifiers developed have a good potential for operational use. However, it would be necessary to advance our methods of automatic patch individualization. In spite of the availability of different procedures, this stage still needs human supervision to obtain reasonable results

ACKNOWLEDGMENT

This study was made possible due PETROBRAS research and development funding.

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