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Oil Spill Identification and Monitoring from Sentinel-1 SAR Satellite Earth Observations: a Machine Learning Approach

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Identification of an oil spill is essential to evaluate the potential spread and float from the source to coastal terrains, and their continued monitoring is essential for managing the environmental protection actions to confine the pollution and avoid further damage. The SAR sensor is perceived as the most significant remote sensing apparatus for the oil slick examination. One of the main aspects of oil spreading over sea surface is that it dampens the capillary waves and so, the backscatter radio waves are suppressed. As a result, oil spills are represented as black spots, while the brighter regions are usually related with unspoiled polluted sea areas. Additionally, the wide coverage that the sensor can provide is highly significant including long-range fate, as well as contextual information, such as sensitive coastal areas or vessels, which can be enclosed in the acquired image. However, oceanic natural phenomena such as low wind speed regions, weed beds and algae blooms, wave shadows behind land, grease ice, etc. can also be depicted as dark spots. These dark regions are commonly categorized as “look-alikes and their discrimination is very challenging. Machine Learning techniques are the most appropriate choice to classify oil spills and look-alikes. In the present work, a comparison between decision trees models and NN is performed to identify and extract the appropriate set of features characterizing an oil spill allowing effective evolution monitoring and setting up proper emergency actions.

1. Introduction

The International Maritime Organization (IMO) estimates that 90% (by volume) and 60% (by economic value) of the world's trade is currently carried by sea. Accordingly, some coastal regions are widely affected by trade routes due to their strategic locations. Oil spills occur as a consequence of accidents, collisions, intentional dumping, or natural causes (Vairo et al., 2018), or during ship loading unloading activities (MIlazzo et al., 2017) and are harmful to marine ecosystems, especially when sensitive areas might be involved (Vairo et al., 2017), impacting as well on economic sectors like fishing, or tourism (Cantorna et al.2019). The occurrence of oil spills has escalated in recent times, due to intensive oil exploration and transportation, which is attributable to increase in demand caused by rapid population growth globally (Yekeen et al., 2019). The severity of oil spills may be increased by the slow response of disaster response teams due to the inability to rapidly identify the source of the spill. Additionally, in case of port and congested areas proximity, a possible escalation to fire scenarios is posed by the presence of actual immediate, or delayed ignition sources (Pesce et al., 2012). Recalling organization resilience pillars, a timely warning for impending risk is of the utmost importance (Pasman et al., 2020), as early warning allows management to be prepared and responding adequately and damage at a given threat may be less deep and recovery more rapid (Vianello et al., 2021). Mitigation associated with oil spill events in sea environment, largely depends upon the design and implementation of adequate contingency plans, which should incorporate the simulation of the spill dispersion patterns and the characterization of marine and coastal areas that could be affected (Palazzi et al., 2004). A model-based emergency response plan, following a major sea accident verified in the Liguria Sea and causing a fuel spill of nearly 600 m^3 was recently proposed (Magrì et al., 2019). According to the approach outlined in the study, the hydrodynamic simulations were tuned on the basis of the images of the spill captured by Copernicus Sentinel-

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1 satellites, obtaining reliable forecasting results. Many authors highlighted the usefulness of Synthetic Aperture Radar images (SAR) obtained by satellites for the detection of oils spills (e.g., Solberg, 2012; Genovez et al., 2017). In a recent study on Deepwater Horizon spill, Garcia-Pineda et al.(2017) scanned and analysed the library of SAR imagery collected during the event to determine which images intersected shorelines and appeared to contain oil: they demonstrated the reliability of the method also in attaining near-shore oiling persistence maps. SAR sensors can scan wide areas, are not affected by clouds and do not depend on solar illumination so that they remain operative at night. To obtain the images, the satellite emits microwaves and subsequently detects the reflected waves. Oil spills affect the marine surface so that the energy reflected towards the satellite is less and appears in images as dark areas. The image analysis is further complicated with phenomena, generally called lookalikes, which have a similar effect and occur in areas with low wind or algae (Fingas and Brown, 2018). These considerations highlight that there is need for a more accurate technique to precisely discriminate the false observations from oil spill to aid prompt decision making in oil spill emergency disaster response situations. To produce false-free oil spill detection maps, several classification methods have been introduced over time. The segmentation classification of oil spills and look-alikes is the most prominent of these approaches, comprising of three stages: dark spots segmentation, where each oil spill candidate is highlighted from the SAR image background, feature extraction, and feature classification (Brekke and Solberg, 2005, Krestenitis et al.2019). The feature extraction is a critical stage in oil spill detection systems; extracted features should have a good discriminatory power to take advantage of the classifier. Feature Selection is a dimensionality reduction technique for obtaining a subset of features that properly describes the given problem. This paper evaluates comparatively a range of clustering, logistic regression and neural network algorithms applied to Sentinel-1 satellites images.

2. Methodology

Machine Learning algorithms offers valid opportunities to automate rapid detection of oil spills and clearly distinguish oil spills from look-alikes thereby overcoming limitations of conventional methods. Neural networks have been largely investigated in real domains for enhancing the generalization capabilities of the classifiers, while discarding the existing irrelevant features (e.g., Mera et al., 2017), Wan and Cheng, 2013) and recognized as robust tools for oil spill classification, even if at the burden of high time computational costs. Moreover, the probability of misclassification does not always decrease as the number of features increases. On these grounds, the present work focuses on developing a machine learning algorithm customized for small-size sample and based on support vector machine (SVM). The main appeal of SVM relies in its ability of achieving highly accurate classification based on limited samples. Upon validation, it has been successfully applied in the classification of remote sensing data allowing the attainment of promising and reliable results (Inglada, 2007, Chi et al., 2008, Maulik et al., 2011), which demonstrate the high potential of SVM as an appropriate classifier tool also for the unexplored domain of oil spill detection.

2.1 Data Acquisition

Sentinel-1 is a constellation of two polar-orbiting satellites, under the EC "Copernicus environmental monitoring program, operating day and night performing C-band synthetic aperture radar imaging, enabling them to acquire imagery regardless of the weather. Since radar measures surface texture, in the images the oil slicks show up well – as black smears on a grey background, while other dark areas show patterns featuring low reflectivity of the radar signal, for instance very calm waters. Sentinel-1 images are used by the European Maritime Safety Agency as part of CleanSeaNet, the European satellite-based oil spill and vessel detection service. Sentinel-1 has also various modes of acquisition. In this study, images in Interferometric Wide Swath mode are used as they provide a wide spatial coverage (250 km swath) in connection with high spatial resolution (5 m × 20 m). The classification framework detailed in the following sections is applied to a dataset consisting in SAR images between 2018 October 8th and 10th, collected from Sentinel 1A Mission and related to the oil spill previously described.

2.2 Machine learning framework

In machine learning, feature selection, or variable selection, is the process of selecting a subset of relevant features (predictors) for use in model construction. Feature selection techniques are used for several reasons:

- easier interpretation of models,
- shorter training times,
- dimensionality reduction,
- reducing overfitting (by reduction of variance)

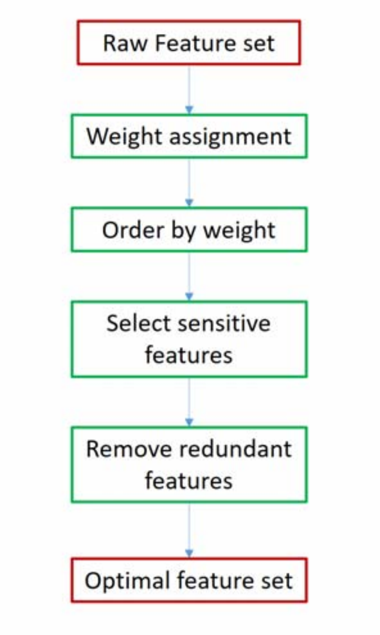


Figure 1: Logic diagram for optimal feature selection

Most of the datasets contain some features that are either redundant or irrelevant and can thus be removed without incurring in a consistent loss of information.
Feature selection techniques are very valuable in domains where there are many features and comparatively few samples (Bermingham et al., 2015).
The feature selection process is summarized in the step-by step block diagram shown in Figure 1.

2.3 Feature selection

Commonly used shallow features for identifying, detecting, and classifying oil spills can be categorized into the following five broad categories (Al-Ruzouq et al., 2020):

- physical (related to the object backscatter value),
- geometric (related to shape),
- texture (related to gray-level),
- contextual (proximity to ships),
- SAR polarimetric (from quad-, dual-, and single-polarimetric images).

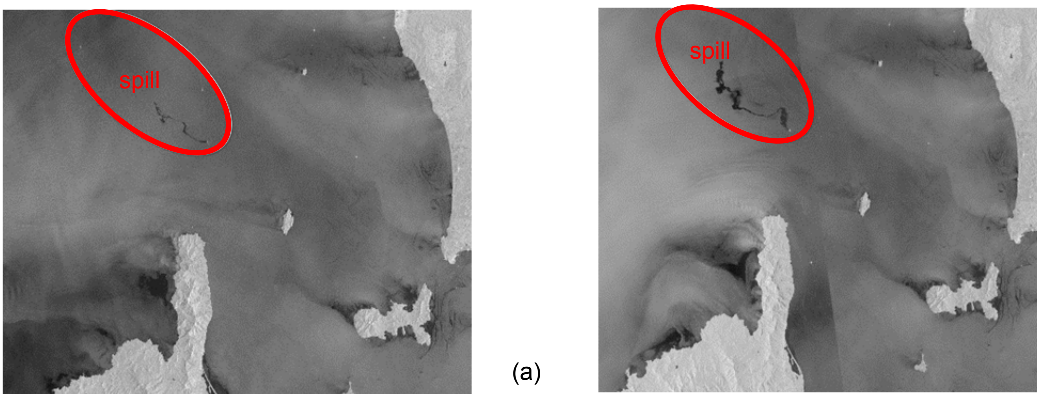
The incorporation of features with reliable discriminatory power contributes to the improvement of classification accuracy in oil spill detection.
The detection of oil spills from optical images mainly focuses on the extraction of statistical, textural, and geometrical features. Spectral, thermal, and textural properties are among the widely extracted features from optical images to differentiate oil spill and surface targets.
The most useful features, which ensure a reliable spill recognition, are geometrical, statistical and contextual one. Indeed, the use of an excessive number of features in a classification scheme may result in the introduction redundant details, increased processing time and reduced classification accuracy. In the present work, the geometrical and contextual characteristics are used. Two morphological characteristics that can best distinguish oil spill and look-alikes for the data-set were determined – complexity (C) and the ratio (R) between length and width of the dark patches. Complexity (C) is the ratio between Perimeter (P) squared and Area (A). Since mineral hydrocarbons have larger tension force compared with seawater, a small amount of oil has usually more regular and smooth boundaries. Morphological characteristics C and R are extracted from the low-level segmentation result. Those features were conveniently used as the training input of the classifier. In the following step, the SVM is used to generate a model for representing these training samples points in space, in order to be classified; the characteristics of dark spots are mapped into the same feature space, and predictions of oil spill or lookalikes can be differentiated based on which side of the space are located (Yu et al., 2014).

Table 1: List of relevant features extracted from SAR images

Feature Category	Feature	Description
Geometric	Area (A)	Area of an image object (in number of pixels)
	Perimeter (P)	Perimeter of an image object (in number of pixels)
	Complexity (C)	Measure of the intricacy of an object geometrical shape
	Spreading (S)	Measures the ratio between an object's width and length
	Shape factor	Measure of an image object border smoothness
	Circularity	Measure of an image object compactness
	P/A	Ratio of the perimeter to the area
Physical	Object standard deviation	Standard deviation of backscatter values an image object computed from SAR imagery
	Object mean value	Mean backscatter values of an image object
	Background mean value	Mean backscatter values of a small region around the object
	Background standard deviation	Standard deviation of backscatter values of a small region around the object
	Max contrast	Difference between background mean value and the lowest backscatter value inside the object
	Object power to mean ratio	Ratio between the standard deviation and the mean of an image object
	Mean contrast ratio	Difference between background mean value and the mean backscatter value of the object
	Gradient standard deviation	Standard deviation of the border gradient
	Mean border gradient	Mean value of the border gradient
	Max gradient	Maximum value of the border gradient
Texture (gray-level)	Contrast	Contrast value computed from backscatter values of image
	Homogeneity	Homogeneity value computed for an image object
	Correlation	Entropy value computed for an image object
	Dissimilarity	Correlation value computed for an image object
	Variance	Dissimilarity value computed for an image object
	Mean	mean value computed for an image object
SAR polarimetric feature	Entropy	Polarimetric parameter used to measure the degree of randomness of the scattering mechanism
	Alpha angle	Polarimetric parameter used to characterize the scattering mechanism of the reflection
	Degree of polarization	Physical parameter characterizing the light polarization degree
	Conformity coefficient	Evaluates if surface scattering is the dominant among all the scattering mechanisms
	Correlation coefficient	Measure that reflects the averaged phase difference among scattering coefficients in co-polarized phases
	Anisotropy	Measures of the relative values of the second and third eigenvalues
	Pedestal height	Measure of the amount of the unpolarized backscattered energy
	Standard deviation	Parameter adopted to differentiate oil and biogenic slicks
Contextual	Number of neighboring targets in the same image	Number of adjacent targets to oil slicks in the same scene
	Distance to ship/rig	Distance from oil slick objects to ship, rig, and oil platforms in the surrounding
	Mean wind speed	Values of mean wind speed of image object

3. Results and discussion

In the following, the capability of the selected features are discussed considering to a recent case-study. On October 7th, 2018 under calm weather and sea conditions (10 m wind speed < 2m/s) with perfect visibility, at 7.00 a.m. ca. two ships collided about 30 km North of Cap Corse and Capraia island, in French waters.



(a) (b)

Figure 2: Oil spill identification based on SAR images on October 8th, 2018, 07:28 (a) and 19:21 (b)

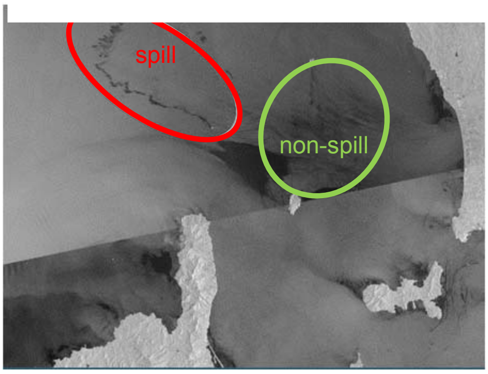


Figure 3: Actual oil spill and look-alike identification based on SAR images on October 9th, 2018, 19:14

The accident involved the Ro-Ro Ulysses, owned and operated by the Tunisian shipping company Cotunav, which ran into the boxship CSL Virginia, owned by Cyprus Sea Lines, while it was anchored about 30 km off the northern tip of Capraia island. The collision caused a major leak of 600 tonnes of fuel covering a major extension of nearly 20 km. On October 8th, 2018, the Copernicus Sentinel 1A mission captured the first satellite images of the oil spill; two visual examples of reliable oil spill identification obtained from first day data acquisition are provided in Figure 2 a and b. Analogously with the findings by Chehresa et al. (2016), this study highlights how an appropriate selection of features can decisively improve the differentiation process between oil spills and look-alikes. A visual example regarding the actual capability of the approach is shown in Figure 3. The optimum set of features for oil spill detection here identified allows to speed-up the feature extraction phase without reducing the classifier accuracy. Increasing the number of extracted features results in a larger search space for finding the optimum set of features, but not always the calculation effort is paid back by a more reliable identification. Increasing the number of samples, indeed, helps in a more substantial validation of the results and can lead to a better evaluation of the obtained optimal set of features. SAR based method properly tuned with the features can be of particular relevance in case of large spatial and temporal spill extent. In particular, novel and improved methods for early warning, prediction of actual risk and safety warranty in the dynamic situation of operation may enable more precise and continuously updated predictions (Pasman et al., 2021) providing a reliable support for critical decision making.

4. Conclusions

The main goal of FS methods is to obtain a relevant subset of features with a good discriminatory power, allowing oil spill detection near shorelines, possibly in sheltered areas, starting from satellite-based SAR imagery. In this study, a SVM classifier was developed to determine the best-selected subset of features for catching and discriminating oil spills. The classifier is applied to the satellite images of a recent spill occurred in an environmental sensitive area, following a ship collision. The selected application demonstrated SVM superior classification capability, especially when training samples are limited. This technique can be used to trace slicks trajectories assessing potential shoreline oil exposure, without resorting to emergency vessel or aircraft. In the context of organizational resilience, the accuracy of oil spill identification represents a crucial factor for effective early warning and for providing actionable information addressing timely emergency response and remediation.

References

Al-Ruzouq R., Barakat M., Shanableh G.A., Khalil A., 2020, Sensors, features and machine learning for oil spill detection and monitoring: a review, Remote Sensing, 12, 3338.

Bermingham M.L., Pong-Wong R., Spiliopoulou A., Hayward C., Rudan I., Campbell H, Wright A.F., Wilson J.F., Agakov F., Navarro P., Haley C.S., 2015, Application of high-dimensional feature selection: evaluation for genomic prediction in man, Sci. Rep. 5, 10312.

Brekke C., Solberg A.H., 2005, Oil spill detection by satellite remote sensing, Remote Sens. Environ., 95, 1-13.

Cantorna D., Dafonte, C. Iglesias, A., 2019, Oil spill segmentation in SAR images using convolutional neural networks. A comparative analysis with clustering and logistic regression algorithms, Applied Soft Computing Journal, 84, 105716.

Chehresa S., Amirkhani A., Rezairad G.A., Mosavi M.R., 2016, Optimum features selection for oil spill detection in SAR image, Journal of the Indian Society of Remote Sensing 44, 129986427.

Chi M., Feng R., Bruzzone L., 2008, Classification of hyperspectral remote-sensing data with primal SVM for small-sized training dataset problem, Adv. Space Res., 41 (11), 1793–1799.

Fingas M., Brown, C.E., 2018, A review of oil spill remote sensing, Sensors, 18, 91.

Garcia-Pineda O., Holmes J., Rissing M., Jones R., Wobus C., Svejkovsky J., Hess, M., 2017, Detection of oil near shorelines during the Deepwater horizon oil spill using synthetic aperture radar (SAR), Remote Sensing, 9 (6), 567.

Genovez P., Ebecken N., Freitas C., Bentz C.,Freitas R., 2017, Intelligent hybrid system for dark spot detection using SAR data, Expert Syst. Appl., 81, 384-397.

Hall, M., Smith, L., 1998. Practical feature subset selection for machine learning, Comput. Sci. 98, 181–191.

Inglada J., 2007, Automatic recognition of man-made objects in high resolution optical remote sensing images by SVM classification of geometric image features. J. Photogrammetry Remote Sens., 62, 236-248.

Krestenitis M., Orfanidis G., Ioannidis K., Avgerinakis K., Vrochidis S., Kompatsiaris I., 2019. Oil spill identification from satellite images using deep neural networks, Remote sensing, 11, 1762.

Ma Y., Zeng K., Zhao C., Ding X., He M., 2014, Feature selection and classification of oil spills in SAR image based on statistics and artificial neural network. IEEE Geoscience and Remote Sensing Symp., 569-571.

Magri S., Quagliati M., De Gaetano P., Vairo T., Fabiano B., 2019, Fuel spill after ships collision: accident scenario modelling for emergency response, Chemical Engineering Transactions, 74, 1363-1368.

Maulik U., Chakraborty D., 2011. A self-trained ensemble with semisupervised SVM: an application to pixel classification of remote sensing imagery, Pattern Recognit. 44 (3), 615–623.

Mera D., Bolon-Canedo, V., Cotos J.M., Alonso-Betanzos A., 2017, On the use of feature selection to improve the detection of sea oil spills in SAR images, Comput. Geosci. 100, 166-178.

Milazzo M.F., Ancione G., Lisi R., 2017, Emissions of volatile organic compounds during the ship-loading of petroleum products: Dispersion modelling and environmental concerns, J. Environ. Manage.,204, 637–650.

Palazzi E., Currò F., Fabiano B., 2004, Simplified modelling for risk assessment of hydrocarbon spills in port area, Process Safety and Environmental Protection, 82(B6), 412-420.

Pasman H.J., Fabiano B., 2021, The Delft 1974 and 2019 European Loss Prevention Symposia: Highlights and an impression of process safety evolutionary changes from the 1st to the 16th LPS. Process Safety and Environmental Protection, 147, 80-91.

Pasman H., Kottawar K., Jain P., 2020, Resilience of process plant: what, why, and how resilience can improve safety and sustainability, Sustainability, 12, 6152.

Pesce M., Paci P., Garrone S., Pastorino R., Fabiano B., 2012, Modelling ignition probabilities in the framework of quantitative risk assessments, Chemical Engineering Transactions, 26, 141-146.

Solberg A.H., Remote sensing of ocean oil-spill pollution, Proc. IEEE 100 (10) (2012) 2931–2945,

Vairo T., Del Giudice T., Quagliati M., Barbucci A., Fabiano B., 2017, From land- to water-use-planning: A consequence-based case-study related to cruise ship risk, Safety Science, 97, 120-133.

Vairo T., Magri S., De Gaetano P., Quagliati M., Fabiano B., 2018, Multicomponent dispersion of hydrocarbons at sea: source term evaluation and hydrodynamic simulation of the spill, Chemical Engineering Transactions, 67, 61-66.

Vianello C., Strozzi F., Mocellin P., Cimetta E., Fabiano B., Manenti F., Pozzi R., Maschio G., 2021, A perspective on early detection systems models for COVID-19 spreading, Biochemical and Biophysical Research Communications, 538, 244-252

Yekeen S., Balogun A., Aina Y., 2019. Early warning systems and geospatial tools: managing disasters for urban sustainability. In: Leal Filho, W., Azul, A.M., Brandli, L., Ozuyar, € P.G., Wall, T. (Eds.), Sustainable Cities and Communities. Springer International Publishing, Cham., CH.

Yu L., Yuanzhi Z., 2014, Synthetic aperture radar oil spills detection based on morphological characteristics, Geo-spatial Information Science, 17, 8-16.