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Object-oriented approach to oil spill detection using ENVISAT ASAR images

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ABSTRACT

The growing importance of oil spill detection as part of a rapid response system to oil pollution requires the ongoing development of algorithms. The aim of this study was to create a methodology for improving manual classification at the scale of entire water bodies, focusing on its repeatability. This paper took an object-oriented approach to radar image analysis and put particular emphasis on adaptation to the specificity of seas like the Baltic. Pre-processing using optimised filters enhanced the capability of a multilevel hierarchical segmentation, in order to detect spills of different sizes, forms and homogeneity, which occur as a result of shipping activities. Confirmed spills detected in ENVISAT/ASAR images were used to create a decision-tree procedure that classifies every distinct dark object visible in SAR images into one out of four categories, which reflect growing probability of the oil spill presence: look-alikes, dubious spots, blurred spots and potential oil spills. Our objective was to properly mark known spills on ASAR scenes and to reduce the number of false-positives by eliminating (classifying as background or look-alike) as many objects as possible from the vast initial number of objects appearing on full-scale images. A number of aspects were taken into account in the classification process. The method's performance was tested on a group of 26 oil spills recorded by HELCOM: 96.15% of them were successfully identified. The final target group was narrowed down to about 4% of dark objects extracted from ASAR images. Although a specialist is still needed to supervise the whole process of oil spill detection, this method gives an initial view, substantial for further evaluation of the scenes and risk estimation. It may significantly accelerate the pace of manual image analysis and enhance the objectivity of assessments, which are key aspects in operational monitoring systems.

1. Introduction

Although spectacular accidental oil spills (e.g. from drilling rigs, oil tankers) can seriously affect marine and coastal environments, they occur only rarely. Even so, a lot of minor shipping-related oil spills have been reported in many seas, for example, the Baltic, where shipping traffic is intense (Kadin, 2008). In contrast to small equipment failures, which are the inevitable result of wear and tear, the illegal dumping of oily wastes into the sea is a serious problem. Regular, small-scale spills contribute to the high overall amount of hydrocarbons released into the environment, and the negative impact of this cannot be underestimated (Fabisiak, 2008). On the other hand, the traceability of perpetrators drops with distance from the land. This is because aerial surveillance has its limitations, resulting from the technical capabilities of helicopters and weather conditions. If weathering processes are intense, a small volume of oil may weather away even before it can be detected by a flight patrol. The method presented here may therefore be a valuable tool in increasing the numbers of offenders brought to justice.

Radars are considered the most appropriate for the operational detection of oil spills. Although they lack ability of discriminating thick oil slicks from thin sheens, which is possible using hyperspectral VIS and TIR remote sensing, radar appears to be the best suited to fulfil the primary response needs of oil spills detection and mapping, because it provides data under all-sky conditions 24/7 due to the negligible effect of cloudiness on recorded images and sun-independence (Issa, 2010; Leifer et al., 2012; Nunziata et al., 2013; Fingas and Brown, 2014; Mihoub and Hassini, 2014). Oil spills are detectable in SAR (Synthetic Aperture Radar) images because

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hydrocarbons affect surface tension and dampen sea surface capillary waves. Therefore, when the radar beam is emitted seawards, it is reflected directly rather than scattered back to the sensor. This local decrease in backscattered energy appears as a dark spot on the image. Hydrocarbons are not the only substances that tend to form continuous films on the sea surface. Phenomena causing misleading look-alikes include grease ice, intensive algal blooms, windless areas known as 'calm areas' and upwelling regions.

The Norwegian company, Kongsberg Satellite Services (KSAT) was one of the first to provide oil spill detection information for the water bodies around Europe. To streamline the service chain and accelerate the response to an oil spill, the European Space Agency (ESA) funded the MarCoast project on marine and coastline surveillance. As a result, the CleanSeaNet service maintained by the European Maritime Safety Agency (EMSA) became operational in 2007. Since then, it has been providing alerts for all the cooperating countries. Similar services were developed independently by the Russian Space Agency (RSA) or the Canadian Space Agency (CSA) (Topouzelis, 2008). To keep up with the dynamic evolution of environmental monitoring systems, intensive work has been carried out on the formulation of automatic, or at least semi-automatic, oil spill detection algorithms (e.g. Haralick, 1983; Solberg et al., 1999; Marghany, 2001; Wu and Liu, 2003; Karathanassi et al., 2006; Topouzelis et al., 2007a). Extensive reviews have been published by Serra-Sogas et al. (2008), Brekke and Solberg (2008), Topouzelis (2008) and Fingas and Brown (2014). Nevertheless, manual inspection still remains the most common technique. Topouzelis (2008) commented that the automatic approach required specific knowledge on image understanding, pattern recognition and classification theories. This is why for widespread use it still needs to be carefully validated on the basis of a much larger dataset than to date. On the other hand, an experiment was conducted amongst professional operators, who had got 32 RADARSAT-1 scenes to interpret. They had not known that oil spills had been already verified by aircraft patrols. From 17 confirmed spills manual operators had correctly classified 15, whilst automatic and semi-automatic methods only 14 and 12 respectively. However, operators had not identified the same spots. Neither had assigned the same confidence levels (probability classes). Moreover, it was estimated that manual inspection took 3–25 min on average (Brekke and Solberg, 2005).

The similarity of signal levels registered in SAR images between oil spills and their look-alikes requires dark spots to be considered in context, and their geometric features to be taken into account as well as contrast with the surroundings. Thus, numerous contemporary methodologies have been derived from pattern recognition theories (e.g. Haralick, 1983). The idea behind all of them remains the same: dark spots in the image have to be distinguished and a number of features established that will permit a distinction between oil spills and their look-alikes. A series of studies with the aim of revealing the most important features of oil spills that would distinguish them from look-alikes were implemented inter alia by Espedal and Wahl (1999), Solberg et al. (1999), and Topouzelis et al. (2003). Topouzelis (2008) published a list of the 25 most frequently repeated features and classified them according their geometrical, physical and textural characteristics. Using a decision tree forest methodology, Topouzelis and Psyllos (2012) found amongst them combination of nine features which give highest classification accuracy and concluded that the most important are two geometrical features characterising *complexity* and *shape*, and one physical characteristics i.e. *local area contrast ratio*. However, the most significant step in the processing chain was the distinction of dark forms: if they are not detected, they cannot be classified. Many techniques have appeared, designed for various forms of use (e.g. Solberg et al., 1999; Del Frate et al., 2000; Wu and Liu, 2003; Karathanassi et al., 2006; Topouzelis et al., 2007a; Kim et al., 2015), but the assumptions underlying them usually constrain them to, e.g. fresh spills surrounded by a homogeneous area (Del Frate et al., 2000). Moreover, a crucial limiting factor was the requirement to define sub-areas or moving windows (Topouzelis and Psyllos, 2012). Their size had an acute influence on results: this became a serious problem in the case of scale-differentiated spills.

In recent years, there has been increasing focus on object-oriented methods combined with multilevel hierarchical segmentation (Karathanassi et al., 2006; Topouzelis et al., 2007b; Bentz et al., 2012). Researches showed a decrease in the number of false alarms noted in comparison to pixel-based approaches (Akar et al., 2011). Otherwise, according to Mera et al. (2014) additional post-processing steps are recommended to improve the shape of detected spills. Multilevel segmentation allows for introduction of mutual relations between objects at the same segmentation level or even at several segmentation levels (defined using several homogeneity criteria) at once, as classifiers. Object-oriented classification seems to be the optimal method for detecting oil spills in SAR images, although certain characteristics may be dependent on input data and should be calibrated for each sensor separately. Topouzelis et al. (2007b) made an initial attempt for ASAR images, but a thorough validation was lacking as this work was based on the analysis of 4 images only.

The objective of this study was to develop a methodology to facilitate the examination of ASAR images covering large areas, which did not require any subarea to be defined and enabled not only fresh oil spills but also blurred ones to be detected. We propose an object-oriented method, based on literature examples, but adjusted and optimised for faster performance through selection of the most effective classifiers. Particular emphasis is placed on adaptation to the specificity of seas like the Baltic, where the location of scattered, rapidly disappearing shipping-derived oil spillages is difficult to predict. Ensuring the repeatability of an assessment is of great importance as well. The results have been validated by oil spills confirmed by HELCOM (Baltic Marine Environment Protection Commission—Helsinki Commission).

2. Materials and methods

2.1. Area of interest

The Baltic Sea is a semi-enclosed water body lying between central and northern Europe (Fig. 1). Although the local crude oil deposits have a significantly lower mining potential compared to global resources, it does not mean there is no risk. There are few oil rigs in the Baltic and hardly any oil pipelines along the bottom of this sea, so the crude oil demand in the countries around the Baltic has to be largely covered by imports. The rapidly increasing maritime traffic is a growing problem. Estimates show that almost 10% of the petroleum hydrocarbons in the Baltic Sea comes from the deliberate dumping of oily waste-water (HELCOM, 2005). Illegal oil discharges occur most frequently in the central Baltic and along shipping routes. Despite their small volume, such regular incidents pose a serious threat to the Baltic ecosystem. Kostianoy et al. (2006) using 247 SAR images (230 RADARSAT/SAR and 17 ENVISAT/ASAR images) identified 274 oil spills connected with shipping activities during the 18 months after June 2004. These spills formed rounded or elongated spots, usually less than 50 km in length.

Look-alikes make SAR data interpretation very difficult, because most of the phenomena that cause errors are commonly observed in the Baltic Sea. The inland character of this water body, the relatively small average depth of 52 m, and high freshwater inputs create favourable conditions for algae, which regularly form