AUTOMATIC DETECTION OF OIL SPILLS WITH LEVEL SET SEGMENTATION TECHNIQUE FROM REMOTELY SENSED IMAGERY

Karantzalos Konstantinos and Argialas Demetre

Remote Sensing Laboratory, Department of Topography, School of Rural and Surveying Engineering, National Technical University of Athens.
karank@central.ntua.gr, argialas@central.ntua.gr

ABSTRACT. The marine environment is under considerable threat from intentional or accidental oil spills, ballast water discharged, dredging and infilling for coastal development, and uncontrolled sewage and industrial wastewater discharges. Monitoring spills and illegal oil discharges is an important component in ensuring compliance with marine protection legislation and general protection of the coastal environments. For the monitoring task an image processing system is needed that can efficiently perform the detection and the tracking of oil spills and in this direction a significant amount of research work has taken place mainly with the use of radar (SAR) remote sensing data. In this paper the level set image segmentation technique was tested for the detection of oil spills. Level set allow the evolving curve to change topology (break and merge) and therefore boundaries of particularly intricate shapes can be extracted. Experimental results demonstrated that the level set segmentation can be used for the efficient detection and monitoring of oil spills, since the method coped with abrupt shape's deformations and splits.

KEY WORDS: remote sensing, environmental monitoring, object detection, image processing, curve evolution, variational methods, Mumford and Shah energy.

1. INTRODUCTION

Today, oil pollution from shipping constitutes one of the environmental concerns on which much international cooperation and law making has taken place, in particular under the auspices of the International Maritime Organisation (IMO). Oil affects living animals and plants both directly and indirectly, as individuals and as members of communities of organisms inhabiting a particular marine environment and interacting with the environment and with each other (Delilah al-Khudhairy, 2002). Currently, there are numerous international treaties and regional conventions that have been adopted to deal with accidental and intentional oil discharges from vessels.

In particular in Europe, which is the world's largest market in crude oil imports representing about one third of the world total, ninety percent of oil and refined products are transported to and from the continent by sea. Some of this oil makes its final way into the sea. Of the oil released by ships, seventy five percent is estimated to have come from operational discharges and only twenty five percent from accidental spills (Indregard et al., 2004). The Mediterranean Sea is characterized as "Special Sea Area" according to MARPOL 73/78 convention and it is protected by Barcelona Convention against discharges from ships. However, Mediterranean is an area under the risk of chronic pollution due to transit shipping routes. Furthermore, while past statistical assessments identified tankers as the main marine polluters with crude oil, recent ones switch the emphasis to fuel oil sludge, bilge water and engine room waste, which are produced by all types of ships.

There are three main ways in which oil tankers and ships illegally discharge oily wastes into the sea (Delilah al-Khudhairy, 2002):

- Oily mixture in ballast water (mainly from oil tankers).
- Oily mixture in cargo tank washings (mainly from oil tankers) resulting from tank cleaning directly into the sea.
- Oily mixture in fuel oil sludge, in engine room effluent discharges and in bilge water (from all types of vessels).

Nowdays SAR data is the most efficient and superior satellite sensor for oil spill detection, though it does not have capabilities for oil spill thickness estimation and oil type recognition (Brekke and Solberg, 2005). RADARSAT-1 and ENVISAT are the two main daily providers of satellite SAR images for oil spill monitoring. Access to an increased amount of SAR images means a growing workload on the operators at image processing centres. Algorithms for automatic detection that can help in screening the images and prioritising the alarms are of great benefit. Research on this field has been ongoing for more than a decade (Bern et al., 1992b; Skøelv & Wahl, 1993; Wahl et al., 1994b; Solberg et al., 2003, Topouzelis et al. 2004). Details for the various methods for radar-based oil spill detection in the marine environment can be found in Brekke and Solberg review paper (Brekke and Solberg, 2005). Automatic identification of oil spills in SAR images is complex because of features that resemble oil spills: look-alikes. Not all-dark sea surface areas in SAR images are real oil slicks. Sea surface may also appear dark due to natural slicks, low wind, certain atmospheric and oceanic phenomena and other reasons. Contextual information such as the shapes and locations of the suspected oil slicks can also help to avoid false detection (Brekke and Solberg, 2005).

In this paper a curve evolution algorithm has been implemented and tested for the automatic oil spill detection, instead of simple or adaptive threshold procedures that have been, mainly, applied in previous efforts (Brekke and Solberg, 2005). In problems of curve evolution, including snakes and active contours, the level set method of Osher and Sethian (1998) has been used extensively because it allows for automatic topology changes, cusps, and corners. These models are based on the theory of curve evolution and geometric flows and in particular on the mean curvature motion of Osher and Sethian (1998) with numerous successful applications for computer vision feature extraction tasks (Osher and Paragios, 2003; Paragios et al., 2005), such as medical image processing for detecting and tracking tumours, in industry for detection tasks during robot controlling processes, in modelling objects or environments, for visual surveillance, ect.

2. METHODOLOGY

2.1 Mumford and Shah segmentation model

One of the main problems of natural and computational vision is to understand how images can be segmented into meaningful and geometrically well behaved observables (Tsai et al. 2001; Paragios et al., 2005). Let $I(x)$ (where x is a bi-variable (x,y)) be an image defined on a domain W without any particular geometrical structure. One of the key features is the segmentation process partitioning W into domains W_i, on which the image I is homogeneous and which are delimited by a system of crisp and regular boundaries (qualitative discontinuities) K.

In Bayesian models, two parts exist: the prior model and the data model. Here, the prior model takes for an a priori the phenomenological evidence of what is qualitatively a segmentation, namely an approximation of image I by piecewise smooth functions u on $W-K$ which are discontinuous along a set of edges K. The aim is to introduce a way of selecting, from among all the allowed approximations (u,K) of I, the best possible one. For this, Mumford and Shah used an energy functional $E(u,K)$ which contains three terms (Mumford and Shah, 1989):

1. a term which measures the variation and controls the smoothness of u on the open connected components W_i of $W-K$,
2. a term which controls the quality of the approximation of I by u,
3. a term which controls the length, the smoothness, the parsimony and the location of the boundaries K, and inhibits the spurious phenomenon of over-segmentation.

The Mumford and Shah (MS) energy is:

$$E(u,K)= \int_{W-K} |\nabla u|^2 dx + \lambda \int_{W} (u-I)^2 + \mu \int_{K} d\sigma \quad (1)$$

Due to the coefficients λ and μ, this MS-model is a multi-scale one: if μ is small, the output is a ''fine grained'' segmentation, if μ is large, the output is a 'coarse grained' segmentation.

As some regularity properties of boundaries can be deduced from the minimizing of E (see below), the third term of the MS-model is given in a more general setting (not a priori regular) by

$H^1(K)=\int_K dH^1$, where H^1 is the length of K in the Hausdorff sense defined by

$$H^1(K)=\sup_{\varepsilon \to 0^+} H^1_\varepsilon(K) \quad \text{with}$$

$$H^1(K)=\inf\left\{ \sum_{i=1}^{i=\infty} diamB_i \mid K \subseteq \bigcup_{i=1}^{i=\infty} B_i, diamB_i \langle \varepsilon \right\} \quad (2)$$

(K is covered in the less redundant way by small disks B_i and is approximated by the diameters of the B_i taking the limit for vanishing diameters).

2.2 Oil spill detection with level set

In this paper, the level set techniques of Osher and Sethian (Sethian, 1996; Osher and Sethian, 1998) is adopted in the implementation of Mumford–Shah active contour model, similar with the energy functional proposed by (Paragios and Deriche, 1998; Chan and Vese, 1999; Tsai et al., 2001). This numerical implementation technique, in conjunction with upwind, conservative, monotone difference schemes (Osher, 1984; Malladi et al., 1995; Sethian, 1996), allows for automatic handling of cusps, corners, and topological changes as the curves evolve.

In general, detection of oil spills can be divided in (Indregard et al., 2004):

- Detection of suspected slicks.
- Manual verification of the slicks (oil/look-alike) and assignment of confidence levels.

In this paper the above described MS curve evolution level set technique is employed for the detection of suspected oil slicks. The developed processing scheme used an advanced variational segmentation technique than a simple or an adaptive threshold. The post-processing analysis, thus, which aiming to separate oil slicks from look-alikes can be simpler but still trivial without avoiding the second step of the manual verification.

Manual verification is an essential step when the developed technique is embedded into an operational oil spill detection system.

The structure of the developed oil spill detection scheme is presented in figure 1.

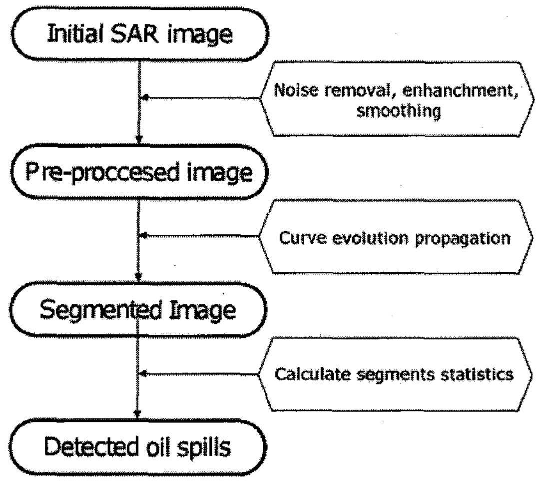

Figure 1. Developed oil spills detection scheme.

Firstly a pre-processing step for the noise removal, image enhancement and smoothing has taken place. The applied pre-processing algorithms are described in Karantzalos and Argialas (2006). The pre-processed image was then embedded in the curve evolution energy minimization functional and the resulting segmented image was obtained. The λ and μ level set coefficients from equation 1, can be tuned optimizing oil spill detection in the following cases where the wind level is known: i) a priori known, ii)is inspected in the image visually or ii)estimated from the SAR image by applying an inverted CMOD45 model (Salvatori et al., 2003). Finally the following statistics were calculated for each of the detected segments: area, perimeter, shape complexity, eccentricity, orientation, segments mean border gradient, inside segments standard deviation and outside segments area standard deviation.

Depending on the above mainly geometric and shape characteristics the final detected oil spills were extracted along with a suggestive assignment of decision's confidence levels.

3. RESULTS AND DISCUSSION

The developed scheme has been applied to a number of SAR images which are available in the CEARAC database of satellite SAR images (CEARAC database, 2003).

In figure 2 and 3 two different (a medium and a more difficult, respectively) oil spill detection cases are shown. In both cases the curve evolution energy functional (equation 1) managed to successfully extract the oil spill boundaries, without tuning λ and μ parameters which was equal to one. The evaluation of the results was done visually with the lack of ground truth observations. In both figures the way that the level set curve is successfully approximating oil spill boundaries is demonstrated.

Furthermore, oil slicks are detected in real time (approximately 15sec. is the computation time for each image in a moderate Pentium IV home computer) and with an efficient detected boundaries precision. The main goal was to investigate level set performance for the detection of possible oil spill and not to the post-processing classification between oil spills and look-alikes. For this task the final manual verification is nowadays still necessary in all operational systems with the consideration, also, that from SAR imagery oil spill thickness estimation and oil type recognition is not possible.

Moreover, level sets have been extensively used for tracking of moving objects in numerous computer vision applications (Karantzalos and Paragios, 2005; Paragios et al., 2005). In the same way, apart from the detection of the oil spills from a single image, level sets can be used for the monitoring and tracking of the slicks in a number of SAR images providing that their geo-reference is known a priori. The detected oil spill segments from the first SAR image can be form the initial curve for the level set propagation in the second image. Thus, the tracking of the slicks could become more robust, fast and effective.

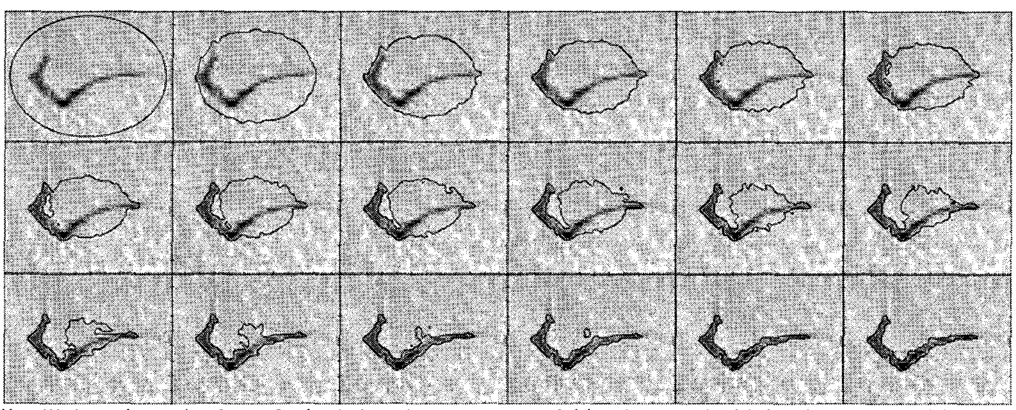

Figure 2. Oil spill detection using Mumford–Shah active contour model implemented with level sets. The initial image and the different steps of the curve evolution propagation are shown, starting from an initial arbitrary elliptical curve leading to the final oil spill detected boundaries. View the figure starting each row from the right.

Figure 3. Different steps of the curve evolution model starting from an initial arbitrary elliptical curve and the final oil spill detected boundaries. View the figure starting each row from the right.

4. CONCLUSIONS & FUTURE PERSPECTIVES

Experimental results showed that level sets can effectively be embedded in a system, which probable oil spills can automatically identified and presented for manual inspection. The developed scheme is currently under qualitative and quantitative evaluation with ground truth data.

References

Bern, T. -I., Wahl, T., Anderssen, T., & Olsen, R. 1992. Oil spill detection using satellite based SAR: Experience from a field experiment. *Proc. 1st ERS-1 Symposium*, Cannes, France, pp. 829– 834.

Brekke C. and Solberg A. H. S., 2005. Oil Spill Detection by Satellite Remote Sensing, *Remote Sens. Environ.*, no.95, pp.1-13.

CEARAC database of satellite SAR images, 2003. http://cearac.poi.dvo.ru/en/db/

Chan T. and Vese L., 1999. An active contour model without edges. *Proceeding of the Second International Conference, Scale-Space '99*. Greece.

Delilah al-Khudhairy, 2002. Marine Oil Pollution: Technologies & Methodologies for Detection & Early warning. Technical Report, EC, Joint Research Centre, 192p.

Indregard, M., Solberg, A., Clayton, P., 2004. D2-report on benchmarking oil spill recognition approaches and best practice. Tech. rep., Oceanides project, EC, Archive No.0410225-A-Doc.

Karantzalos K . and Argialas D., (to be published in 2006) "Improving edge detection and watershed segmentation with anisotropic diffusion and morphological levelings", *International Journal of Remote Sensing*.

Karantzalos K. and N. Paragios, 2005. Implicit free-form-deformations for multi-frame segmentation and tracking, *IEEE VLSM-ICCV05*, China.

Malladi R., Sethian J., and Vemuri B., 1995. Shape modeling with front propagation: A level set approach, *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 17, pp. 158–175.

Mumford D. and Shah J., 1989. Optimal approximation by piecewise smooth functions and associated variational problems, *Comm. Pure Appl. Math.* 42, pp577–685.

Osher S. and Paragios N., 2003. *Geometric Level Set Methods in Imaging Vision and Graphics,* Springer Verlag, ISBN 0387954880.

Osher S. and Sethian J., 1988. Fronts propagation with curvature dependent speed: Algorithms based on Hamilton-Jacobi formulations, *J. Comput. Physics*, vol. 79, pp. 12–49.

Osher S., 1984. Riemann solvers, the entropy condition, and difference approximations, *SIAM J.* Numer. Anal., vol. 21, pp. 217–235.

Paragios N. and Deriche R., 1998. Geodesic Active Regions for Texture Segmentation, INRIA Research Report 3440.

Paragios N., Chen Y. & Faugeras O., 2005. *Handbook of Mathematical Models of Computer Vision*, Springer, ISBN 0387263713.

Salvatori, L., Bouchaib, S., Frate, F. D., Lichtenneger, J., & Samara, Y., 2003. Estimating the wind vector from radar SAR images when applied to the detection of oil spill pollution., *CoastGIS'03*.

Sethian J., 1996. *Level Set Methods: Evolving Interfaces in Geometry*, Fluid Mechanics, Computer Vision, and Material Science. Cambridge, U.K.: Cambridge Univ. Press.

Skoelv A. and Wahl, T., 1993. Oil spill detection using satellite based SAR, Phase 1B competition report. Tech. rep., Norwegian Defence Research, Establishment.

Solberg, A. H. S., Dokken, S. T., & Solberg, R., 2003. Automatic detection of oil spills in Envisat, Radarsat and ERS SAR images. *Proc. IGARSS'03,* vol. 4 (pp. 2747–2749).

Topouzelis, K., Karathanassi, V., Pavlakis, P., Rokos D., 2004. "Oil spill detection using RBF neural networks and SAR data", *XXth Congresss of the International Society for Photogrammetry and Remote Sensing*, Instabul.

Tsai A, Yezzi A, Willsky A, 2001. Curve Evolution Implementation of the Mumford-Shah Functional for Image Segmentation, Denoising, Interpolation, and Magnification, *IEEE Transactions on Image Processing,* vol. 10, no. 8, pp. 1169-1186.

Wahl, T., Skbelv, 2., & Andersen, J. H. S., 1994. Practical use of ERS-1 SAR images in pollution monitoring. *Proc. IGARSS'94*, vol. 4, pp. 1954– 1956.