Oil Spill Segmentation
of SAR ImagesVia Graph Cuts

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Abstract— **Segmentation of dark patches in SAR images is an important step in any oil spill detection system. Segmentation methods used so far include 'Adaptive Image Thresholding', 'Hysteresis Thresholding', 'Edge Detection' (see [1] and references therein) and entropy methods like the 'Maximum Descriptive Length' technique [2]. This paper extends and generalizes a previously proposed Bayesian semi-supervised segmentation algorithm [3] oriented to oil spill detection using SAR images. In the base algorithm on which we build on, the data term is modeled by a finite mixture of Gamma distributions, with a given predefined number of components, for modeling each one of two classes (oil and water). To estimate the parameters of the class conditional densities, an expectation maximization (EM) algorithm was developed. The prior is an M-level logistic (MLL) Markov Random Field enforcing local continuity in a statistical sense. The methodology proposed in [3] assumes two classes and known smoothness parameter. The present work removes these restrictions. The smoothness parameter controlling the degree of homogeneity imposed on the scene is automatically estimated and the number of used classes is optional. To extend the algorithm to an optional number of classes, the so-called α-expansion algorithm [4] has been implemented. This algorithm is a graph-cut based technique that finds efficiently (polynomial complexity) the local minimum of the energy, (i.e, a labeling) within a known factor of the global minimum. In order to estimate the smoothness parameter of the MLL prior, two different techniques have been tested, namely the Least Squares (LS) Fit and the Coding Method (CD) [5]. Semi-automatic estimation of the class parameters is also implemented. This represents an improvement over the base algorithm [3], where parameter estimation is performed on a supervised way by requesting user defined regions of interest representing the water and the oil. The effectiveness of the proposed approach is illustrated with simulated SAR images and real ERS and ENVISAT images.**

Index Terms - segmentationg; bayesian; oil spill detection; SAR; MERIS.

I. INTRODUCTION

Segmentation of dark patches in SAR images is an important step in any oil spill detection system and many different approaches to the problem have been proposed so far. These approaches are built on off-the-shelf segmentation algorithms such as 'Adaptive Image Thresholding', 'Hysteresis Thresholding', 'Edge Detection' (see [1] and references therein) and entropy based methods like the 'Maximum Descriptive Length' technique [2].

Work [3] introduces a Bayesian segmentation algorithm where the observed data (oil and water) data is modeled by a finite Gamma mixture, with a given predefined number of components. To estimate the parameters of the class conditional densities, an expectation maximization (EM) algorithm was developed. The used prior is a second order Markov Random Field (MRF), more specifically an MLL (Multi-Level Logistic) model. To estimate the labels, the posterior distribution is maximized (MAP) via graph-cut techniques [4].

Notwithstanding the promising results provided by the above described segmentation method, it has restrictions that the present work overcomes. The first restriction concerns the number of classes that is limited to two. The second restriction concerns the smoothness parameter that has to be manually tuned. Furthermore, the class parameters estimation process is completely supervised, requiring an interaction with the user in order to manually select a region containing oil pixels and a region containing water pixels.

In the present work we generalize [3] by: (1) extending the number of segmented classes to a predefined optional number c, (2) automatically estimating the smoothness parameter β in the MRF, and (3) automatically estimating the class parameters θ. To extend [3] to an optional number of classes, the so-called α-expansion algorithm [4] is implemented. In order to estimate the smoothness parameter β, two different techniques are tested, namely the Least Squares (LS) Fit and the Coding Method (CD) [5]. A first attempt is carried out to implement unsupervised segmentation using a semi-supervised initialization.

Two algorithms are proposed in this work: 'Algorithm 1', implements the extension to an optional number of classes and the extension to the smoothness parameter estimation; 'Algorithm 2' implements also the unsupervised class parameters estimation.

To evaluate the accuracy of the proposed algorithms, different simulations have been carried out. For details on the simulations results, addressing both the Gaussian and the

Gamma model and both algorithms, please refer to [7]. In the present work, one simulation of 'Algorithm 1' using the Gamma data model is given. Furthermore, results of segmenting real SAR and MERIS images using 'Algorithm 1' are also provided. Hereby the Gamma mixture data model proposed in [3] is adopted to model the observed SAR intensity values. For the MERIS image, a multivariate Gaussian distribution is used.

The article is organized as follows: Section II gives a short overview of the original algorithm that builds the base to this work; Section III describes, in pseudo-code, the main steps of the proposed segmentation methods; Section IV presents simulation and real results, and finally Section V contains concluding and future work remarks

II.   OVERVIEW OF BAYESIAN ALGORITHM

The algorithm proposed in [3] finds a labeling f for a set of N pixels $P := \{1, 2, …, N\}$. A labeling $f := \{f_1, f_2, … f_N\}$ is a mapping from P to L, where $L := \{1, 2, …, c\}$ is the set of labels. The vector $y := \{y_1, y_2, … y_N\}$ stands for the observed data, corresponding to the image intensity measurements at the pixels.

In order to infer $\hat{f}$, we adopt the MAP criterion. This amounts to maximize the posterior density of the labeling given the observed data. As described in [3] in detail, this is equivalent to minimizing the objective function

$$E(f_1,...,f_N) = \sum_{p=1}^{N} E^p(f_p) + \sum_{p<j} E^{p,j}(f_p,f_j) , \qquad (1)$$

where $p, j \in P$ are pixel locations, E^p is the negative likelihood given by

$$E^p(f_p) = -\log(p(y_p \mid f_p, \theta_{f_p})), \qquad (2)$$

when $p(y_p|f_p, \theta_{fp})$ is the conditional density of y_p given f_p and given the class parameters θ_{fp}, called data model or sensor function, and $E^{p,j}$ is the negative likelihood of the prior. Since we have adopted a MLL, i.e.,

$$\log(p(f)) = E^{p,j}(f_p,f_j) = -\beta\delta(f_p,f_j) , \qquad (3)$$

where (p,j) is a 2-pixel clique. In expression (3), δ is the discrete delta function and β controls the degree of homogeneity we wish to impose on the scene. Please note that

$$\sum_{p<j} E^{p,j}(f_p,f_j) = -\beta \, nrNeighbours(f), \qquad (4)$$

with

$$nrNeighbours(f) = \sum_{i=1}^{N} n(f_i), \qquad (5)$$

where $n(f_i)$ is the number of neighbors in neighborhood N_i having the same label as pixel i.

As demonstrated in [3], $E(f_1, … f_N)$ is *graph representable* for c = 2 and, in these circumstances, the global minimum of the objective function may be computed by applying the graph-cut algorithm described in [4].

When applying the described Bayesian algorithm to a MERIS image, the adopted data model $p(y_p|f_p, \theta_{fp})$ changes from a Gamma mixture to a multivariate Gaussian distribution described by:

$$\frac{1}{(2\pi)^{N/2}|\Sigma_p|^{1/2}} \exp\left(-\frac{1}{2}(y_p - \mu_p)^T \Sigma_p^{-1}(y_p - \mu_p)\right), \qquad (6)$$

In equation (6), $y_p = [y_{p1},…y_{pN}]$ are the values of the MERIS channels (N = 13, for level 2 processing) and $\theta_{fp} = [\mu_p, \Sigma_p]$ are the data model parameters. For the MERIS segmentation described in this article, the model parameters have been learned in a supervised way by defining regions representing the classes and computing ML estimators.

III.   PROPOSED SEGMENTATION METHODS

In the next sections we propose supervised and unsupervised approaches to the segmentation. The first approach assumes known class parameters, whereas the second does not. In both methods the smoothness parameter is assumed unknown.

A.   Supervised Segmentation with Beta Unknown

In the first segmentation method, we have adopted iterative labeling-estimation, with the two steps (step 2.1 corresponding to the labeling and step 2.2 corresponding to the estimation) being performed alternately. The EM algorithm provides a justifiable formalism for such a scheme [5]. The initial values for the labeling and the parameter estimator are optional and don't seem to have a relevant influence in the final performance. Since the class parameters θ have been estimated as described in [3], they are assumed known and are omitted from the pseudo-code.

The algorithm may be run with the LS or with the CD estimation technique.

Algorithm-1:

```
1. Start with an arbitrary initial labeling f_0
and arbitrary parameter β̂ = β_0

2. While |Δβ̂| ≤ δ or nrIter < ItMaxNr do
    2.1 Find f̂ = α_Expansion(f_0 , β̂)
    2.2 Find β̂ = LS_Estimation(f̂) or
               CodingMethod(f̂)

3. Return (f̂ , β̂)
```

B.   Unsupervised Segmentation with Semi-Supervised Initialization

In this second method, we have also adopted iterative labeling-estimation as in 'Algorithm-1', but now the class parameters are also iteratively estimated. The initialization of the class parameters θ is performed in a semi-automatic way: the user provides a region of pixels corresponding to one (for

example the most frequent: water) of the classes (class1). This region is then used to estimate the ML (Maximum Likelihood) parameters of the class1 distribution. In a second step, pixels are clustered in two sets, class1 and not-class1, by applying a simple threshold to the estimated distribution. Then, the parameters of the remaining classes are initialized by applying an EM mixture estimation procedure to the pixels clustered in the not-class1 set.

Algorithm-2:

```
1. Start with an arbitrary parameter β̂=β₀ and
arbitrary initial labeling f₀
2. Provide initial class parameter estimations
θ̂=θ₀
3. Provide initial f̂=α_Expansion(f₀,β₀,θ₀)
4. While |Δβ̂|≤δ or nrIterations < ItMaxNr do
        4.1 Find θ̂ = ML_Estimation(f̂)
        4.2 Find f̂ = α_Expansion(f₀,β̂,θ̂)
        4.3 Find β̂= LS_Estimation(f̂,θ̂)or
                 CodingMethod(f̂,θ̂)
5. Return (f̂,β̂,θ̂)
```

IV. RESULTS: SIMULATED AND REAL IMAGES

This Section presents results for simulated and for real SAR images. For simulated images, a Gamma data term is used. Although the presented results are restricted to one Gamma mode per class, the developed procedure also works with Gamma mixtures as developed in [3].

A. Simulated Images

A simulated image of three classes corrupted by Gamma noise ($\theta_l = (a_l, \lambda_l)$, a_l and λ_l being the Gamma distribution parameters, with $l \in L$) is used. The ground-truth is 'hand-made' and contains structures resembling those that may be found in oil-spill scenarios. 'Algorithm 1' as described in Section II is used, both with the LS and the CD estimation methods. The algorithm segmentation is compared with the results given by the best achievable segmentation using α-expansion, corresponding to tuning the β parameter manually.

Each test is run three times and the mean values of the overall accuracies (OA) corresponding to the percentage of correct label are computed. To assess the segmentation performance, we compare the algorithm OA with that obtained without the MRF prior, i.e., $OA_{no\ prior}$ for β=0. Figure 1 shows the obtained results.
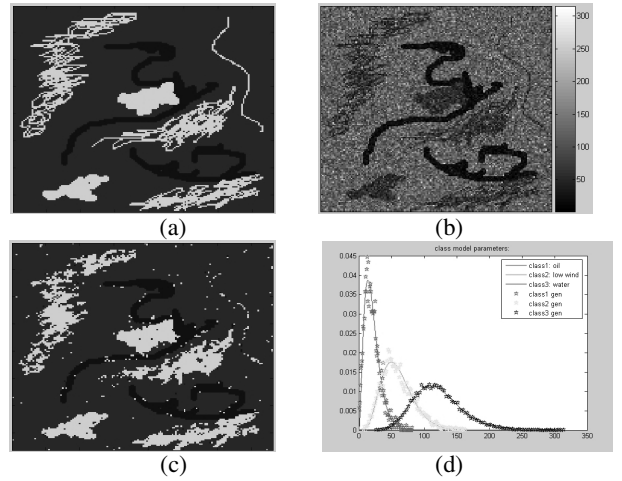

Figure 1. (a) Ground-truth (b) Simulated image (c) Segmentation result using 'Algorithm-1': LS estimated β = 0.4213, OA = 95.3%. Best achievable OA for this image = 95.4%. $OA_{no\ prior}$ is 83.2% (d) Probability functions used to generate the image with superimposed histogram of generated data set.

B. Real Images

The 'Algorithm-1' has been applied to a real ERS-1 SAR image fragment. The scene (frame 2367, orbit 17211) containing the fragment has been acquired on 30 October 1994, and covers several oil platforms in the Norwegian and British sector of the North Sea. The image has been radiometric calibrated and corrected for the incidence angle effect. We have assigned a class to 'oil', a class to 'water' and a class to 'platform' and learned the class parameters using the supervised method described in [3]. Figure 2 displays the obtained results after applying 'Algorithm-1'. The image has also been segmented by applying the method described in [6] for comparison. Following the described method, an image pyramid of two levels was created and the threshold was set adaptively based on the PMR value calculated in a local window of 100 pixels x 100 pixels. After the thresholding, morphological operators have been applied in order to remove segmented patches with area less than 50 pixels.

'Algorithm-1' has also been applied to a pair of simultaneously acquired Envisat MERIS/ASAR images containing an oil spill.

The image pair, a MERIS Full Resolution level2 and an ASAR Image Mode image has been acquired on 19 July 2004, in the ocean between Cyprus and Lebanon. The occurrence of the oil spill (centered on ≈ 33ºN, 33º39'E) was documented on the Oceanides project database and it was expected to find evidence of the circa 10 km long dark patch in the cloud-free MERIS image. In fact, a dark patch of the expected size, form and orientation was detected on the MERIS image but centered on ≈ 34º28'N, 35ºE. The pixels flagged as clouds have been masked before the segmentation process. Although we can not conclude that the segmented patch is the oil spill due to the location difference, the segmentation results are reported in Figure 3.
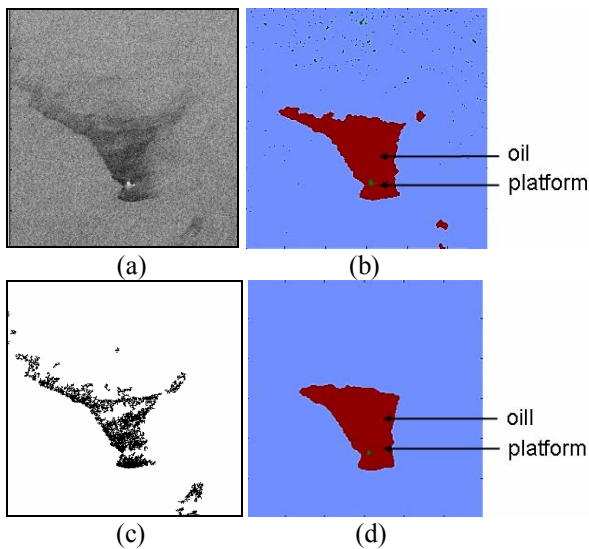
Figure. 2. (a) ERS image: intensity values (b) Segmentation with LS; (c) Segmentation using 'Adaptive Thresholding' followed by morphological operations (d) Segmentation with CD.

V. CONCLUSIONS

The first results of applying the proposed methodology to simulated images with Gamma data models and to real SAR data are promising. With 'Algorithm-1', high OA accuracies have been achieved for simulated images.

By applying 'Algorithm-1' to a real ERS image, we have been able to successfully segment a platform of reduced size, the water and the oil. No post-processing to remove small areas has been applied to the results. Hereby, the CD estimation method seems to provide a better segmentation than the LS method, contrarily to what happened for simulated images, where the LS method provided slightly better results (see [7]). The segmentation of the three regions was not possible to achieve with 'Adaptive Thresholding', where post-processing was needed to remove small false segmented areas.

The Envisat ASAR Image has also been successfully segmented with 'Algorithm-1' (see Figure 3 (c)). Regarding the MERIS image, although we have no ground-truth, the methodology seems to be applicable for segmenting homogeneous regions in general, e.g. algae patches.

These are preliminary results and more tests, with more trials per test, are required to fully determine the accuracy of the proposed methods. The algorithms should be tested with more real SAR and MERIS images containing validated oil spills. Furthermore, tests addressing the case of more than three classes should be performed and 'Algorithm-2' should be tested on real images. More recent parameter estimation techniques should be considered for the smoothness parameter estimation step.
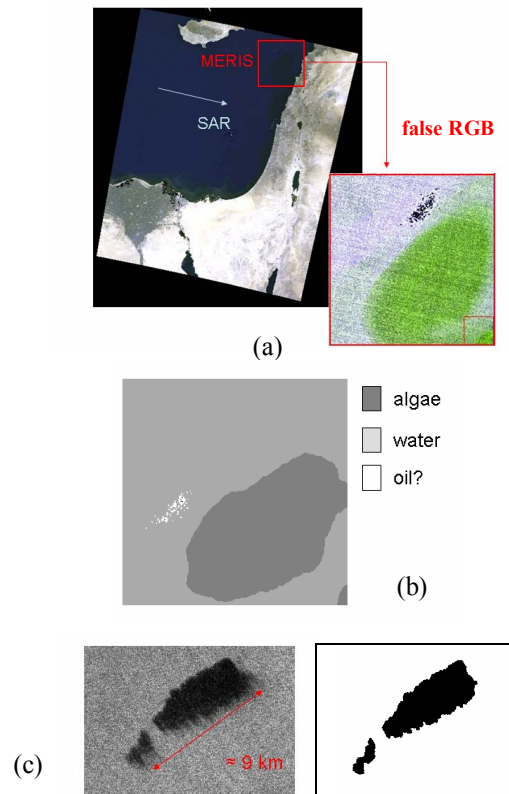

Figure. 3. (a) Image location (b) MERIS Segmentation with 'Algorithm-1' (c) ASAR Segmentation with 'Algorithm 1'

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