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Level Sets with One Dot Fuzzy Initialization for Marine Oil Spill Segmentation

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***Abstract*—Image segmentation techniques are widely used for identifying marine oil spill regions in SAR images, with one representative technique being level set evolution. The accuracy of level set evolution highly relies on a proper initial level set function which roughly captures the marine oil spill layouts in a SAR image. However, marine oil spill regions are always complicatedly shaped, and it is time-consuming and impractical to manually devise precise initial level set functions for various marine oil spill shapes. In order to address this problem and achieve efficient and robust segmentation, we develop a one dot initialization scheme for level set evolution. Our method just requires an arbitrary pixel within one marine oil spill region as initialization. It exploits fuzzy connectedness between pixels such that consistent initial level set functions can be established via arbitrary initial dots within the marine oil spill region. Experimental results validates the robustness of our strategy.**

I. Introduction

In recent decades, marine oil spill accidents have frequently occurred at different scales and have caused various damages to the natural environment [1]. It is vital to monitor the oil spills in a timely manner for the purpose of both damage assessment and spread control. Satellite-based synthetic aperture radar (SAR) [2], due to its capacity of all-weather and all-time operation, plays an important role in monitoring marine oil spills [3]. How to develop intelligent algorithms for segmenting marine oil spill regions from SAR images has been an important research topic in the literature of ocean remote sensing.

Straightforwardly applying basic image processing techniques, such as gray level thresholding, results in practical solutions to marine oil spill segmentation tasks. Furthermore, in order to characterize the complicated spatial layouts of oil spills, the energy minimization [4] based segmentation algorithms have recently been widely exploited. Ren et al. [5] have developed a discrete energy minimization framework based on a dual-smoothing strategy for marine oil spill segmentation. Xia et al. [6] have developed a continuous energy functional that is minimized through level set evolution for obtaining optimal marine oil spill contours.

Though the energy minimization comprehensively encodes the contextual information for oil spill regions, their effectiveness heavily relies on the prior knowledge about oil spill and background regions. Specifically, the level sets for oil spill segmentation require the prior knowledge of an initial contour (i.e., initial level set function) for computing the energy minimization and achieving the final oil spill segmentation [7]. One widely accepted way for initializing level set evolution is to employ a regular contour such as a rectangle box which roughly and maybe partially surrounds an object. Though level sets initialized by similar regular contours (e.g. rectangle boxes) tend to result in almost identical results for normal object segmentation, slightly different initial contours may lead to totally different segmented oil spill regions. This is because unlike regularly formed normal objects, one oil spill region usually manifests itself in an irregular shape with an arbitrary curved contour [8]. Regular initial contours such as rectangle boxes are not sufficient to characterize the sophisticatedly shaped oil spills. For instance, Fig. 1(a) alternately illustrates four marine oil spill SAR images and their manually segmented oil spill regions. Figs. 1(b) and 1(c) illustrate two different initial contours (the white boxes overlaid on the SAR images) for each of the four SAR images, and their corresponding segmented oil spill regions based on the region scalable fitting (RSF) level set method [9].

It is clear from Figs. 1(a), 1(b) and 1(c) that the accuracy of the region scalable fitting (RSF) level set method is sensitive to initial contours, especially for segmenting complicated shaped regions such as oil spills. If the initial contours are manually developed in an inconsistent manner, they cannot guarantee the segmentation accuracy. On the other hand, a precise initial contour with respect to the oil spill region is supposed to improve the segmentation accuracy of the level set method. However, manually devising precise initial contours for various marine oil spills tends to be time consuming such that the effectiveness of level set in auto-segmentation is neutralized. This shortcoming refrains the level set based energy minimization methods from achieving robust performance in practice.

In order to address the above mentioned problems and achieve efficient and robust segmentation, in this paper we develop a one dot initialization scheme for level set evolution. Our method just requires an arbitrary pixel within one marine oil spill region as initialization. It exploits fuzzy connectedness between pixels such that consistent initial level set functions can be established via arbitrary initial dots within the marine oil spill region. We use the initial contour thus obtained for driving the RSF level set evolution, in order to achieve robust segmentation results for marine oil spills.

II. Region Scalable Fitting Level Sets

This section describes the classical region scalable fitting (RSF) level set method [9]. Section II-A presents the energy functional formulation of image segmentation problems. Section II-B presents the evolution scheme for optimizing the energy functional.

A. Energy Functional

For an image I with its pixel at (x, y) denoted as $I(x, y)$, the level set methods employ a level set function $\phi(x, y)$ as a segmentation indicator. Geometrically, ϕ manifests itself as a surface in a three-dimensional space. In numerical computation, ϕ can be thought of a matrix with the same size as the image I. For an optimal level set function, $\phi(x, y) \geq 0$ indicates that the pixel $I(x, y)$ is segmented into the object (e.g. marine oil spill) region, otherwise it is segmented into background. The curve obtained in terms of the intersection between ϕ and the zero plane (i.e. $\phi(x, y) = 0$) is referred to as the zero level set of $\phi(x, y)$, and it indicates the contour of an object. RSF is an approach to establishing an energy functional (i.e., objective function) with respect to ϕ. The RSF energy functional is defined as follows:

$$\begin{aligned} E_\epsilon(\phi, q_1, q_2) = &\sum_{i=1}^{2} \lambda_i \iint \Big(\iint \omega_i M_i^\epsilon\big(\phi(u, v)\big) \mathrm{d}u\mathrm{d}v \Big) \mathrm{d}x\mathrm{d}y \\ &+ \nu \iint \big| \triangledown H_\epsilon\big(\phi\left(x, y\right)\big) \big| \mathrm{d}x\mathrm{d}y \end{aligned} \tag{1}$$

where $\omega_i = K_\sigma(x-u,\ y-v) \left| I\left(u, v\right) - q_i\left(x, y\right) \right|^2$ with K_σ being a nonnegative kernel function and σ being its scale parameter. Additionally, $M_1^\epsilon\left(\phi\right) = H_\epsilon\left(\phi\right)$, $M_2^\epsilon\left(\phi\right) = 1 - H_\epsilon\left(\phi\right)$, and $H_\epsilon\left(\phi\right)$ is a smooth function defined as follows:

$$H_\epsilon\left(\phi\right) = \frac{1}{2}\left[1 + \frac{2}{\pi}\arctan\left(\frac{\phi}{\epsilon}\right)\right] \tag{2}$$

The derivative of $H_\epsilon\left(\phi\right)$ is:

$$\delta_\epsilon\left(\phi\right) = H_\epsilon^{'} = \frac{1}{\pi}\frac{\epsilon}{\epsilon^2 + \phi^2}. \tag{3}$$

To preserve the regularity of the level set function and maintain a stable level set evolution, it is necessary for the energy functional to involve a level set regularization term $R\left(\phi\right)$ as follows:

$$R\left(\phi\right) = \iint \frac{1}{2}\left(\left|\triangledown\phi\left(x, y\right) - 1\right|\right)^2 \mathrm{d}x\mathrm{d}y. \tag{4}$$

The overall RSF energy functional is:

$$F\left(\phi, q_1, q_2\right) = E_\epsilon\left(\phi, q_1, q_2\right) + \eta R\left(\phi\right) \tag{5}$$

where η is a positive balancing parameter.

B. Level Set Evolution for Energy Minimization

The basic idea of the level set method is to formulate the contour motion as the evolution of a level set function for the purpose of minimizing the energy functional (5). The functions q_1 and q_2 that minimize the energy functional $F\left(\phi, q_1, q_2\right)$ for a fixed ϕ satisfy the following Euler-Lagrange equations:

$$\iint K_\sigma(x-u,\ y-v) M_i\big(\phi(u,v)\big)\left[I(u,v) - q_i(x,y)\right] \mathrm{d}u\mathrm{d}v = 0 \tag{6}$$

and $q_i(x, y)$ is obtained as follows:

$$q_i\left(x, y\right) = \frac{K_\sigma\left(x, y\right) * \left[M_i^\epsilon\big(\phi\left(x, y\right)\big) I\left(x, y\right)\right]}{K_\sigma\left(x, y\right) * M_i^\epsilon\big(\phi\left(x, y\right)\big)}, i = 1, 2. \tag{7}$$

The functions q_1 and q_2 are the weighted averages of the pixel intensities in a neighborhood of (x, y), and the size of q_i is proportional to the scale parameter σ.

Keeping q_1 and q_2 fixed, we use the standard gradient decent method to minimize the energy functional $F\left(\phi, q_1, q_2\right)$ with respect to ϕ, and the required partial derivative is:

$$\begin{aligned} \tfrac{\partial F}{\partial \phi} = &\ \delta_\epsilon\left(\phi\right)\left(\lambda_1 e_1 - \lambda_2 e_2\right) - \nu \delta_\epsilon\left(\phi\right) \mathrm{div}\left(\tfrac{\triangledown\phi}{\left|\triangledown\phi\right|}\right) \\ &- \eta\left[\triangledown^2\phi - \mathrm{div}\left(\tfrac{\triangledown\phi}{\left|\triangledown\phi\right|}\right)\right] \end{aligned} \tag{8}$$

where e_1 and e_2 are the functions as follows:

$$e_i\left(x, y\right) = \iint \omega_i \mathrm{d}u\mathrm{d}v, i = 1, 2. \tag{9}$$

The gradient descent update for ϕ is:

$$\phi_t(x, y) = \phi_{t-1}(x, y) - \alpha \frac{\partial F}{\partial \phi}\bigg|_{t-1} \tag{10}$$

where α is the learning rate.

One widely accepted initial level set function for the evolution (10) is established in terms of a rectangle box roughly surrounding an object (e.g. marine oil spill region). The convergence of the level set evolution according to (7) and (10) achieves the minimization of the region scalable fitting (RSF) energy functional (5). Detailed explanations about the RSF level sets can be found in [9]. The zero level set of the converged level set function yields the contour for the marine oil spill region in one SAR image.

III. One Dot Fuzzy Initialization

Though the RSF level set is reasonably formulated and achieves state of the art segmentation performance in various image processing tasks, its accuracy highly relies on the initial level set function for the evolution (10), especially for segmenting irregular shapes such as marine oil spill regions. Different initial level set functions may result in tremendously different marine oil spill segmentation results. To guarantee accurate segmentation, it is expected that the initial contour consistently follows the marine oil spill boundary. In the light of this observation, we propose a one dot fuzzy initialization strategy which exploits the fuzzy connectedness [10] between pixels and is capable of establishing consistent initial contours via different initial dots within one marine oil region.

We commence by computing the fuzzy adjacency $\rho_{i,j}$ between the pixels at (x_i, y_i) and (x_j, y_j) as follows:

$$\rho_{i,j} = \begin{cases} \frac{1}{1+k_1 d_{i,j}},\ d_{i,j} \leq 1; \\ \\ \quad 0 \quad ,\ \mathrm{otherwise}. \end{cases} \tag{11}$$

where $d_{i,j} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}$ represents the distance between the two pixels and k_1 is a nonnegative constant.

Then the fuzzy affinity $a_{i,j}$ between the pixels at (x_i, y_i) and (x_j, y_j) is defined as:

$$a_{i,j} = \frac{\rho_{i,j}}{1 + k_2 \left| I\left(x_i, y_i\right) - I\left(x_j, y_j\right) \right|} \tag{12}$$

where k_2 is a nonnegative constant.

Suppose that the one dot used as the prior knowledge within the oil spill region is at (x_0, y_0) in the SAR image. We compute the fuzzy connectedness $\mu_{(x_0,y_0)}(x, y)$ [10] of one pixel at (x, y) with respect to the selected initial dot at (x_0, y_0):

$$\mu_{(x_0,y_0)}\left(x, y\right) = \max_{p \in P} \left(\min_{(i,j) \in p} a_{i,j} \right) \tag{13}$$

where P denotes the set of all possible paths between the pixel at (x_0, y_0) and the pixel at (x, y), and p denotes an individual path between the pixel at (x_0, y_0) and the pixel at (x, y). Here, a path is a sequence of nearby pixels, and in (13) $a_{i,j}$ denotes the fuzzy affinity of a pair of nearby pixels at (x_i, y_i) and (x_j, y_j) along the path p. The computation of (13) can be performed in terms of dynamic programming.

We define the initial level set function $\phi_0\left(x, y\right)$ with $t = 0$ as follows:

$$\phi_0\left(x, y\right) = \begin{cases} +2, & \mu_{(x_0,y_0)}\left(x, y\right) \geq \theta; \\ -2, & \mu_{(x_0,y_0)}\left(x, y\right) < \theta. \end{cases} \tag{14}$$

where θ is an empirical thresholding parameter. The zero level set of $\phi_0\left(x, y\right)$ is the initial contour.

We refer to our level set initialization scheme as one dot fuzzy initialization, because it just requires one pixel within the marine oil spill region as the prior knowledge and it exploits fuzzy connectedness to establish an initial level set function. The fuzzy connectedness characterizes the global relations between pixels in terms of feature similarity and spatial adjacency. The initial contour derived via the fuzzy connectedness with respect to one initial dot thus follows the global spatial layout of the marine oil spill and is insusceptible to the variation of initial dot location within the oil spill region. Furthermore, the initial level set function based on fuzzy connectedness characterizes the irregular shapes of oil spills and provides a high quality initialization for level set evolution. The level set evolution (10) refines the resulted initial contour (14) and achieves the final accurate segmentation.

IV. Experimental Validation

To validate the effectiveness of the proposed initialization scheme, we test our strategy on four SAR images containing differently shaped marine oil spill regions. We conduct the initializations by using two slightly different rectangle boxes (illustrated in Figs. 1(b) and (c)) and two different arbitrary dots within one marine oil spill region (illustrated in Figs. (d) and (e)) for each image. The two slightly different initial contours for each image result in the segmentations with considerable differences. The one dot fuzzy initialization scheme overcomes this deficiency such that the segmentation results for each image based on the two different initial dots are quite identical. Furthermore, the segmentation results in Figs. (d) and (e) derived from one dot fuzzy initialization are much more accurate than those in Figs. 1(b) and (c) derived from the initial box contours.

V. Concluding Remarks

In contrast to existing energy minimization schemes which require considerable amount of prior knowledge about oil spill and background, the one dot fuzzy initialization just uses one dot as prior knowledge. Therefore, it is efficient and is less dependent on manual manipulation than existing level set methods. Furthermore, the one dot fuzzy initialization exploits the fuzzy connectedness between pixel and establish global characterization which favors robust segmentation.

The proposed strategy involves two separate steps, i.e, initial contour generation based on one dot fuzzy initialization and level set evolution. In our future work, we will investigate how to embed the one dot fuzzy initialization into the level set energy functional to achieve a more reasonable balance between initialization and evolution for marine oil spill segmentation.

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References

[1] P. F. Kingston, "Long-term environmental impact of oil spills," *Spill Science & Technology Bulletin*, vol. 7, no. 1, pp. 53–61, June 2002.

[2] A. H. Solberg, C. Brekke, and P. O. Husoy, "Oil spill detection in radarsat and envisat sar images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 45, no. 3, pp. 746–755, March 2007.

[3] B. Fiscella, A. Giancaspro, F. Nirchio, P. Pavese, and P. Trivero, "Oil spill detection using marine sar images," *International Journal of Remote Sensing*, vol. 21, no. 18, pp. 3561–3566, december 2000.

[4] G. Chung and L. A. Vese, "Energy minimization based segmentation and denoising using a multilayer level set approach," in *International Workshop on Energy Minimization Methods in Computer Vision and Pattern Recognition*. Springer, 2005, pp. 439–455.

[5] P. Ren, M. Di, H. Song, C. Luo, and C. Grecos, "Dual smoothing for marine oil spill segmentation," *IEEE Geoscience and Remote Sensing Letters*, vol. 13, no. 1, pp. 82–86, January 2016.

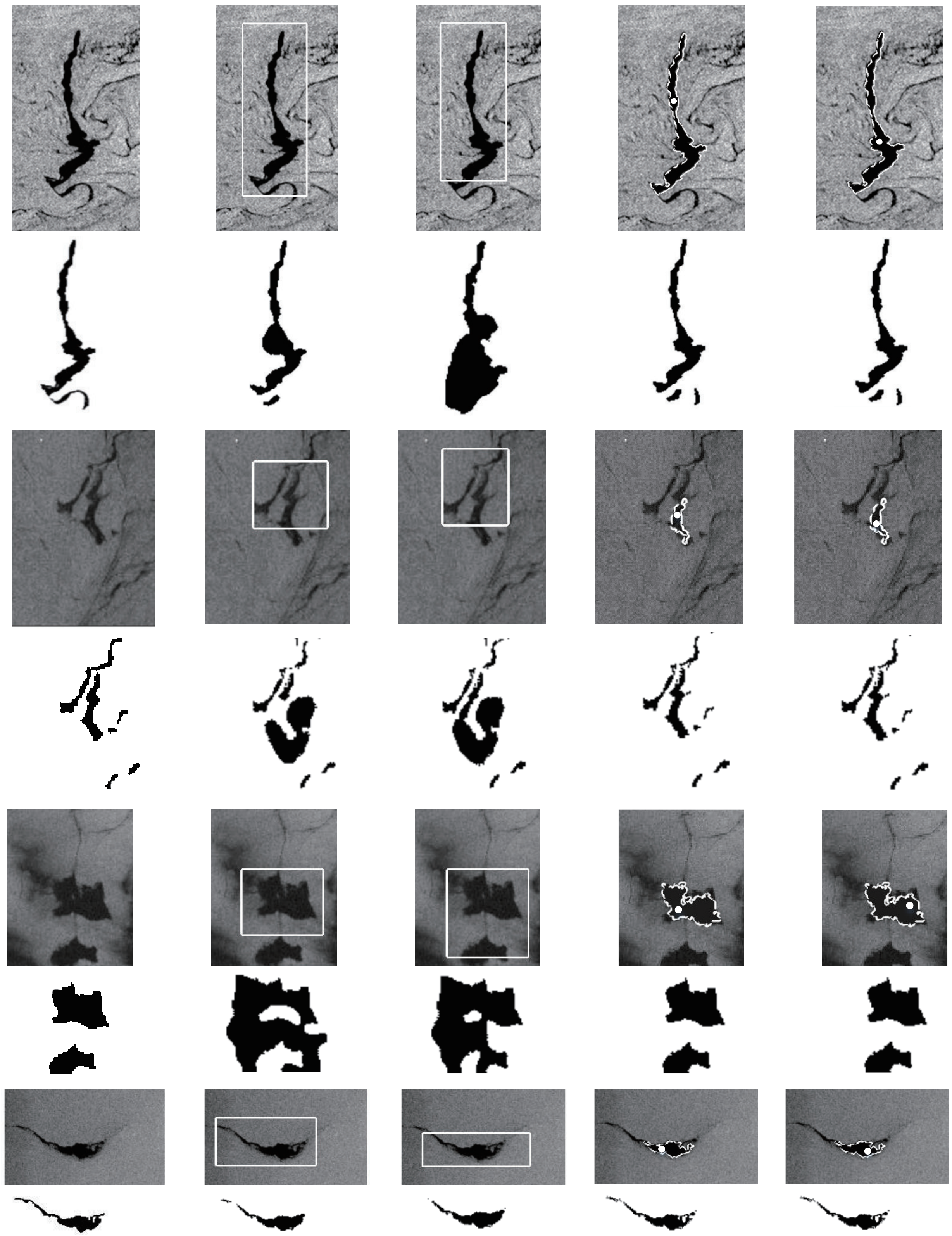
[6] G.-S. Xia, G. Liu, W. Yang, and L. Zhang, "Meaningful object segmentation from sar images via a multiscale nonlocal active contour model," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 54, no. 3, pp. 1860–1873, March 2016.

[7] N. Paragios and R. Deriche, "Geodesic active contours and level sets for the detection and tracking of moving objects," *IEEE Transactions on pattern analysis and machine intelligence*, vol. 22, no. 3, pp. 266–280, 2000.

[8] M. Airouche, L. Bentabet, and M. Zelmat, "Image segmentation using active contour model and level set method applied to detect oil spills," in *Proceedings of the World Congress on Engineering*, vol. 1, no. 1. Lecture Notes in Engineering and Computer Science, July 2009, pp. 1–3.

[9] C. Li, C.-Y. Kao, J. C. Gore, and Z. Ding, "Minimization of region-scalable fitting energy for image segmentation," *IEEE transactions on image processing*, vol. 17, no. 10, pp. 1940–1949, October 2008.

[10] J. K. Udupa and S. Samarasekera, "Fuzzy connectedness and object definition: theory, algorithms, and applications in image segmentation," *Graphical models and image processing*, vol. 58, no. 3, pp. 246–261, May 1996.



(a) (b) (c) (d) (e)

Fig. 1. Segmentation results: (a) illustrates an original SAR image and the manual segmented oil spill region; (b) and (c) illustrate two different initial level set functions (i.e. initial contours displayed as white boxes overlaid on the SAR images) and their segmented oil spill regions; (d) and (e) illustrate two initial dots (displayed as white solid dots within the oil spill regions) along with their derived initial contours (displayed as white dash lines overlaid on the SAR images), and their segmented oil spill regions.