Abstract—Robust and accurate segmentation of the oil slick from SAR imagery is a key step for the detection and monitoring of oil spills, whose observation is very important for protecting the marine environments. However, intensity inhomogeneity, noise, and weak boundary often exist in the oil slick region in SAR imagery, making the accurate segmentation of oil slick very challenging. In this paper, we propose a novel statistical active contour model for oil slick segmentation. First, we fit the distributions of the inhomogeneous intensity with Gaussian distributions of different means and variances. Then, a moving window is used to map the original image intensity into another domain, where the intensity distributions of inhomogeneous objects are still Gaussian but are better separated. In the transformed domain, the means of the Gaussian distributions can be adaptively estimated by multiplying a smooth function with the signal within the window. Thereafter, for each local region, we define a statistical energy function, which combines the smooth function, the level set function, and the constant approximating the true signal from the corresponding object. In addition, in order to make the final segmentation robust to the initialization of level set function, we present a new energy function which is convex with respect to the initialization of level set function, thereby avoiding the local minima. An efficient iterative algorithm is then proposed to minimize the energy function that makes the segmentation robust. Experiments undertaken using some challenging SAR oil slick images demonstrate the superiority of our proposed algorithm with respect to the state-of-the-art representative methods.

Index Terms—Intensity inhomogeneity, level set method, oil spills, segmentation.

I. INTRODUCTION

NOWADAYS, the marine environment and ecology are confronting serious threat from oil spills on the sea surface, which are mainly caused by illegal oily discharges from ships and tankers, oil spill accidents, and offshore installations. In order to control the oil pollution, it is crucial to detect and monitor the oil spills. Synthetic aperture radar (SAR) satellite sensors provide an efficient and cost-effective solution for this purpose. Compared with the airborne sensors, the space-borne SAR sensors are particularly useful for situations involving searching large areas or observing sea surface at night and cloudy weather conditions [1]–[3].

A general framework for detecting oil slick in single-polarization intensity SAR image often includes three important procedures [1], [4]: dark spot detection/region selection, feature extraction and oil spill and look-alike classification, which can be achieved by corresponding segmentation techniques, feature extraction algorithms and classification methods, respectively. Obviously, the segmentation is an important step in this whole detection process, because if a slick is detected well during segmentation, the effective features can be well extracted and further the correct classification can be achieved. Moreover, if the oil spills can be successfully separated from lookalikes (i.e., other dark patches such as grease ice, rain cells, and shear zones [5], which are caused by the natural phenomena dampening the short waves on the surface), it is very easy to extract the slick features, such as the area, the perimeter, and the width [1]. There are have been many good performances reported for oil slick detection using single-polarization intensity SAR image, but it is difficult to discriminate the oil slick from biogenic films in some cases. The polarimetric SAR can solve this limitation by using features computed from dual-pol or quad-pol images, thereby being widely studied in recent years [5]–[7].

Generally, the oil spill images have the following characteristics: 1) the shape of the oil slick is not fixed because of the influence of winds, flows and tides [8]; 2) the oil is usually dark in SAR images because of the dampening effect on the Bragg waves [4]; 3) the boundary of the oil slick is often very weak and blurring due to the low contrast between the seawater and the oil slick [8]; and 4) the intensity inhomogeneity often occurs [9]. The intensity distributions between the oil slick region and the seawater have serious overlap because of the intensity inhomogeneity of the oil slick, causing the accurate segmentation of oil slick to be a very challenging task. This intensity overlapping mainly depends on the following conditions [10], [11]: 1) oil-related parameters, e.g., its viscoelastic properties; 2) sea state conditions; and 3) sensor’s parameters, e.g., frequency and spatial resolution.

For the speckled noise in an SAR image, tailored edge-detectors (e.g., constant false alarm rate (CFAR) [12]) can be directly applied to the original image domain. For the traditional edge detection methods, they should be applied to the de-speckled image domain. Most of the traditional edge detection methods (e.g., canny edge detector [13] and LoG edge detector [14]) need to link the edge points into a continuous edge, which is difficult to implement in most cases because of the large break of the edges [9]. Furthermore, these edge detectors [13],...
[14] are sensitive to the noise, which results in lots of false alarms that are difficult to eliminate. In order to yield robust segmentation, researchers proposed region-based segmentation approaches which are based on the statistical property of the image intensity, such as fuzzy c-means algorithm [15], wavelet methods [16], and level set method [17]. These widely used region-based segmentation methods often assume that the image intensity is uniform in each segmented region. However, when these models are applied to real images with intensity inhomogeneity such as the SAR oil slick images, severe misclassifications will occur.

Jing et al. [9] recently proposed a novel global minimization active contour model (GMACM), which is based on a convex region scale fitting (RSF) model [18] for oil slick segmentation with promising results. However, the GMACM only takes into account the local-intensity means, which is not sufficient to accurately model an image with intensity inhomogeneity, especially when the intensity means in different regions are similar [17]. To avoid this limitation, we propose a novel globally statistical active contour model (GSACM) that takes into account the local average and variance of image intensities. The main idea of our GASCM method is as follows: by exploiting the image’s local redundant information, we define a mapping from the original image domain to another domain such that the intensity probability model is not only more robust to noise but also better separated for each object. This transformation can be seen as an image domain filter (IDF) technique [19] which convolves the image with a low-pass filter for anti-noise. A similar anti-noise method was also used in the classical SAR edge detector (e.g., CFAR [20]) that defines the difference of the average pixel values of two nonoverlapping neighborhoods. Different from the IDF method, another anti-noise method that is widely used in SAR images is the multilooking method, which reduces speckle noise using spatial/spectral averaging. We then devise a statistical energy function for the distribution of each local region in the transformed domain, which combines the smooth function, the level set function, and the constant neighboring region center on it, i.e., \( O_x \) is a neighboring region center on it, i.e., \( O_x = \{ y \mid |y - x| \leq \rho \} \), where \( \rho \) is the radius of the region \( O_x \). There are two categories of objects (i.e., open water and oil slick) with different statistical distribution in the SAR oil slick image. With \( \Omega_t \) being the domain of the \( t \)th object, the whole image domain \( \Omega \) can be represented as \( \Omega = \bigcup_{t=1}^{2} \Omega_t \), with \( \Omega_1 \cap \Omega_2 = \emptyset \). We define a mapping \( M : I(x) \rightarrow \tilde{I}(x) \) from the original image-intensity domain to another domain as follows:

\[
\tilde{I}(x) = \frac{1}{m_t(x)} \sum_{y \in \Omega_t \cap O_x} I(y)
\]

where \( m_t(x) = |\Omega_t \cap O_x| \). The noise in the SAR image is speckled, and the latter is a multiplicative noise. Thus, \( I(x) = s(x)z(x) \), where \( s(x) \) denotes the true signal and \( z(x) \) the speckle noise. The speckle noise is caused by the interaction between the coherent radar illumination and rough scattering surfaces [19]. We can use an additive model to represent the multiplicative noise model as \( I(x) = s(x) + n(x) \), where \( n(x) \) is a nonstationary signal-dependent additive noise which can be
assumed to be Gaussian distributed [26]. The distribution of intensity \( I \) for each region \( \Omega_i \) is

\[
p(I(y)|c_i, \sigma_i) = \frac{1}{\sqrt{2\pi\sigma_i}} \exp\left(-\frac{(I(y) - \mu_i(x))^2}{2\sigma_i^2}\right)
\]

where \( u_i(x) \) is the spatially varying mean and \( \sigma_i \) is the standard deviation. The mean \( u_i(x) \) can be approximated as \( u_i(x) \approx b(x)c_i \) [27], where \( b(x) \) is a smooth function and \( c_i \) is the true constant signal in the domain \( \Omega_i \). We assume that the intensity of pixels is independently distributed [28], so the corresponding probability density function (PDF) of intensity \( I \) is still a normal distribution [29] with \( I(x|c_i, \sigma_i) \sim N(\mu_i, \sigma_i^2) \). Thus, the profile of the distribution is suppressed because the standard deviation is smaller than that of the original distribution (i.e., \( \sigma_i/\sqrt{m_i(x)} < \sigma_i \)).

Since the intensity inhomogeneity manifests itself as a smooth intensity variation across an image [30], we can assume that \( I(y|c_i, \sigma_i) \approx I(x|c_i, \sigma_i), \forall y \in \Omega \). We have

\[
p(D|\alpha) = \prod_{i=1}^{2} p(I(x|c_i, \sigma_i))^{m_i(x)} \approx \prod_{i=1}^{2} p(I(x|c_i, \sigma_i))^{m_i(x)} \sim N(\mu, \gamma)
\]

where \( D = \{I(x|c_i, \sigma_i), i = 1, 2\} \), \( \alpha = \{c_i, \sigma_i, i = 1, 2\} \), and

\[
\mu = \gamma \frac{\sum_{i=1}^{2} m_i(x)\mu_i}{\sigma_i^4} \quad \text{and} \quad \gamma = 1 - \frac{\sum_{i=1}^{2} m_i(x)}{\sigma_i^2}
\]

Obviously, we can see that each pixel is composed of multiple classes of intensities in (4); thus, by utilizing (3), our model can yield a soft classification result. Moreover, as can be seen from (1), the intensity in the transformed domain exploits the information about neighboring pixels belonging to the same class, so its classification result is less sensitive to noise and can yield a smoother border.

We integrate the likelihood function (3) over the entire image domain to define the following energy function:

\[
E(\alpha) = -\int_{\Omega} \log p(D|\alpha) dx
\]

\[
= \text{constant} - \sum_{i=1}^{2} \int_{\Omega} \int_{\Omega_i} \log p(I(y|c_i)) dy dx
\]

\[
= \sum_{i=1}^{2} \int_{\Omega} \int_{\Omega_i} K_\rho(x, y) \left( \log(\sigma_i) + \frac{(I(y) - b(x)c_i)^2}{2\sigma_i^2} \right) dy dx
\]

where \( K_\rho(x, y) \) be the indicator function of region \( \Omega_i \). We can utilize a level set function \( \phi \) to represent the regions inside and outside of the contour \( C \) as \( \Omega_1 = \text{inside}(C) = \{ \phi < 0 \} \) and \( \Omega_2 = \text{outside}(C) = \{ \phi > 0 \} \). and \( \Omega_2 \), respectively. The energy function \( E(\alpha) \) can be rewritten as

\[
E(\alpha, \phi) = \sum_{i=1}^{2} \int_{\Omega} d_i(y)M_i(\phi) dy + TV(\phi)
\]

where \( d_i(y) = \frac{1}{\Omega} K_\rho(x, y)(\log(\sigma_i) + (I(y) - b(x)c_i)^2/2\sigma_i^2) dy dx \), \( \alpha = \{c_i, \sigma_i, i = 1, 2\} \), \( M_1(\phi) = H(\phi), M_2(\phi) = 1 - H(\phi) \), \( H(\phi) \) is the Heaviside function, and \( TV(\phi) = \int_{\Omega} |\nabla \phi| dx \) is a total variation (TV) term to regularize the level set function.

### B. Energy Minimization With Respect to the Variables in \( \alpha \)

The minimization of (6) with respect to each variable in \( \alpha \) can be obtained by fixing other variables, yielding the closed forms of solutions as follows:

\[
\hat{c}_i = \frac{\int_{\Omega} (K_\rho * b)M_i(\phi) dy}{\int_{\Omega} (K_\rho * b^2)M_i(\phi) dy}
\]

\[
\hat{\sigma}_i = \frac{\sum_{k=1}^{2} K_\rho \ast M_k(\phi)}{\sum_{k=1}^{2} K_\rho \ast M_k(\phi)} \cdot \frac{\sigma_k^2}{\sigma_i^2}
\]

\[
\hat{\phi}_i = \sqrt{\frac{\int_{\Omega} K_\rho(y)M_i(\phi(y))(I(y) - b(x)c_i)^2 dy dx}{\int_{\Omega} K_\rho(y)M_i(\phi(y)) dy dx}}
\]

The deviations of (7)–(9) can be readily obtained by calculus of variations.

### C. Level Set Evolution Formulation

However, when \( \alpha \) is fixed, the energy function (6) with respect to the level set function is non-convex because is non-convex on the domain \( \Omega \) [31]. Therefore, the final segmentation result may be influenced by the initial condition of the level set function. We will propose a new approach to achieving the global minimization of (6) while fixing the parameter set \( \alpha \). According to [31], (6) is equivalent to the following constrained convex energy function:

\[
E(\phi) = TV(\phi) + \lambda \int_{\Omega} (d_1 - d_2) \phi dx, \text{ s.t. } 0 \leq \phi \leq 1
\]

Equation (10) is equivalent to the convex regularization problem [31]

\[
\min_{\phi, \varphi} E_{\phi, \varphi}^{CSACM} = \int_{\Omega} |\nabla \phi| dx + \frac{1}{2\theta} \int_{\Omega} (\phi - \varphi)^2 dx + \int_{\Omega} \nu(\varphi) dx + \lambda \int_{\Omega} (d_1 - d_2) \varphi dx
\]

where \( \nu(\varphi) = \max\{0, 2|\varphi| - 1, 0\}, \theta > 0 \) is a small fixed parameter.

As \( E_{\phi, \varphi}^{CSACM} \) is a convex function, we can achieve its optimal solution by iterating \( \phi \) and \( \varphi \) separately. The iteration process is as follows.
Step 1) Fix $\varphi$, minimizing the following problem:

$$\min_{\psi} E_{\varphi, \psi}^{\text{GS ACM}} = \int_\Omega \nabla \psi \, dx + \frac{1}{2\theta} \int_\Omega (\psi - \varphi)^2 \, dx \quad (12)$$

Step 2) Fix $\phi$, minimizing the following problem:

$$\min_{\psi} E_{\phi, \psi}^{\text{GS ACM}} = \frac{1}{2\phi} \int_\Omega (\phi - \varphi)^2 \, dx + \phi \int_\Omega \nu(\varphi) \, dx + \lambda \int_\Omega (d_1 - d_2) \varphi \, dx \quad (13)$$

The gradient descent flow for (12) can be obtained as

$$\phi_t = \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) - \frac{\varphi - \psi}{\theta}. \quad (14)$$

In the following, we use the efficient approach proposed by [31] to solve (14), deriving the solution as follows:

$$\phi = \varphi - \theta \cdot \text{div}(\hat{p}) \quad (15)$$

where $\hat{p}$ is solved using a fixed point method by setting $\hat{p}^0 = (0, 0)$, iterating the following equation:

$$\hat{p}^{n+1} = \hat{p}^n + \Delta t \left( \frac{\text{div}(\hat{p}^n)}{1 + \Delta t \cdot \nabla \text{div}(\hat{p})} \right) - \varphi / \theta \quad (16)$$

with $\Delta t \leq 1/8$ to ensure convergence.

Based on [31, Prop. 4], the solution of (13) is achieved as follows:

$$\varphi = \min \{ \max (\varphi - \theta \lambda (d_1 - d_2), 0), 1 \}. \quad (17)$$

The Heaviside function $H(\phi)$ in $d_1$ and $d_2$ is given as follows [31]:

$$H(\phi) = \begin{cases} 1, & \phi > \kappa \\ 0, & \text{else} \end{cases} \quad (18)$$

where $\kappa = (\lambda, 1)$ is almost an arbitrary fixed parameter. In our experiments, we set $\kappa = 0.5$.

D. Summary of the Algorithm

Based on the above descriptions of our algorithm, the procedures are summarized in Table I.

IV. COMPARISON MODELS

We compare our algorithm with the RSF model [18] and GMACM method [9], which are two state-of-the-art ACMs. Here, we first briefly introduce the RSF model. Then, we give a detailed explanation about the GMACM which is the state-of-the-art ACM applied to oil slick segmentation.

A. RSF Model

Li et al. [18] proposed the RSF model which embeds the local image information into an energy function to deal with images with intensity inhomogeneity. The basic idea of RSF model is that it introduces a kernel to control the local region scale via minimizing the following energy function:

$$E_{C, f_1, f_2}^{\text{RSF}} = \lambda_1 \int_{\Omega \text{ inside}(C)} G_\sigma(x - y) \cdot I(y) - f_1(x) \frac{1}{2} \, dy \, dx + \lambda_2 \int_{\Omega \text{ outside}(C)} G_\sigma(x - y) \cdot I(y) - f_2(x) \frac{1}{2} \, dy \, dx \quad (19)$$

where $\lambda_1 > 0$ and $\lambda_2 > 0$ are fixed parameters, $I : \Omega \rightarrow R$ is an input image, $G_\sigma$ is a truncated Gaussian kernel with standard variance $\sigma$, and $f_1, f_2$ are two smooth functions that approximate the local image intensities inside and outside the contour $C$, respectively. The level set method is then applied to optimize $E_{C, f_1, f_2}^{\text{RSF}}$ by representing the contour $C$ using the zero level set of a Lipschitz function (i.e., the level set function) $\phi(x) : \Omega \subseteq R$. Then, minimizing the energy function $E_{C, f_1, f_2}^{\text{RSF}}$ with respect to $\phi$, we derive the local fitting functions $f_1$ and $f_2$ are represented as follows:

$$f_1(x) = \frac{G_{\sigma + H(\phi)} I(x)}{G_{\sigma + H(\phi)} + H(\phi)} \quad (20)$$

with $H(\cdot)$ in (20) a Heaviside function.

Obviously, $f_1$ and $f_2$ of (20) are the weighted averages of the pixel intensities in a Gaussian window inside and outside the contour, respectively, that’s why the RSF model can handle images with intensity inhomogeneity. However, only these weighted averages cannot fit the image intensity well, especially when the intensity means in different regions are similar [23]. Moreover, the RSF model easily falls into local minima, leading to unsatisfactory segmentation results [refer to Fig. 2(c)].
B. GMACM Model

Recently, Jing et al. [9] proposed a global minimization ACM (GMACM), which is a convex version of RSF model, and applied it to segment oil slick. The GMACM energy functional is

$$E_{u, f_1, f_2, \nu}^{\text{GMACM}} = \int_{\Omega} g(x) \left| \nabla u(x) \right| \, dx + \lambda \int_{\Omega} \left| v_2(x) - e_1(x) \right| \, v(x) \, dx$$

$$+ \frac{1}{2} \| u - \nu \|_{L_2}^2, \text{ s.t. } 0 \leq u(x) \leq 1$$  \hspace{1cm} (21)

where

$$e_1(x) = \int_{\Omega} G_\sigma(y - x) \, I(x) - f_1(y) \| \, dy,$$

$$e_2(x) = \int_{\Omega} G_\sigma(y - x) \, I(x) - f_2(y) \| \, dy,$$

and $g(x) = 1/(1 + |\nabla I(x)|^2)$ is an edge detector function, $\lambda > 0$ is a fixed parameter. Then, the minimization of $E_{u, f_1, f_2, \nu}^{\text{GMACM}}$ is achieved by iterating the following two steps.

1) Fix $u$, minimizing $E_{u, f_1, f_2, \nu}^{\text{GMACM}}$ with respect to $u$ by solving the following equation:

$$u = v - d|\nabla (\tilde{p})|$$  \hspace{1cm} (22)

where $\tilde{p}$ can be achieved by iterating the following equation:

$$\tilde{p}_{n+1} = \tilde{p}_n + \tau \left( \nabla \left( d|\nabla (\tilde{p}_n) | - v_n \right) \right)$$  \hspace{1cm} (23)

where $\tau$ is the iteration step.

2) Fix $u$, minimizing $E_{u, f_1, f_2, \nu}^{\text{GMACM}}$ with respect to $v$ by solving the following equation:

$$v = u - \lambda (e_2 - e_1).$$  \hspace{1cm} (24)

However, from steps 1) and 2), we can see that this minimization method omits the constrained term $0 \leq u(x) \leq 1$ in (21), which may cause the obtained solution $u$ not to fall into the feasible domain $0 \leq u(x) \leq 1$. Moreover, similar to the RSF model, the GMACM also only utilizes the local mean information to fit the image intensity, which is inaccurate in some cases. However, our method can yield much more accurate results than both RSF model and GMACM [refer to Fig. 2(d) and (e)].

V. EXPERIMENTAL RESULTS

Here, we compare our method with the RSF model [18] and the GMACM [9], which are representative of the state-of-the-art ACMs for image segmentation. For our model, we set $\theta = 0.01$, $\lambda = 0.1$, $\Delta t = 0.1$, $\kappa = 0.5$, and initialize $\bar{c}_i, \bar{\sigma}_i (i = 1, 2)$, and $\bar{h}$ randomly for all of the experiments. In most of the following experiments, the initialization of the level set function is binary.

A. Data Sets

We utilize ten SAR oil slick images available from CEARAC SAR image database,1 and six SAR oil slick images from an oil spill incident in the Gulf of Mexico in April to May, 2010.2 These images have been preprocessed (converting the original SAR data to a common format and geographical projection) and masked (to mask away all land areas). All 16 SAR images contain strong speckle noise and suffer from serious intensity inhomogeneity. The ground truth results are from manual segmentation undertaken by expert SAR image analysts. The experiments from Fig. 1 to Fig. 4 show the qualitative segmentation results which may be somewhat subjective to define a better segmentation results.

B. Comparisons of Robustness to the Level Set Initialization

The SAR image used in this experiment is the ENVISAT C-band SAR data collected on May 12, 2010, at 15:55:02 UTC in the Gulf of Mexico. Fig. 1 shows the segmentation results on this image with different level set initializations using our algorithm, the RSF method [18], and GMACM [9]. The top row shows different level set initializations. The second row shows the results of RSF method. The third row shows the results of GMACM method. We can see that most of oil edges have been detected. However, the final results are dependent on the level set initializations. The fourth row shows the results of GMACM method. These results are somewhat subjective to define a better segmentation results.


C. Comparisons With RSF and GMACM

Here, we compare our algorithm with RSF model and GMACM method using ten SAR oil slick images available from CEARAC SAR image database and six SAR oil slick images from an oil spill incident in the Gulf of Mexico. Because the RSF model and GMACM method are sensitive to the level set initializations, we tune the level set initializations for them to yield the best performance. Then, we utilize the same level set initialization as RSF or GMACM for our method for fair comparison.

Fig. 2 demonstrates the segmentation results by RSF, GMACM and our algorithm for an SAR oil slick image with different regions scales. This experiment is related to the ENVISAT C-band SAR data collected on April 29, 2010, in the Gulf of Mexico. From Fig. 2(c) and (d), we can observe that both RSF and GMACM yield unsatisfying results due to the reasons we have discussed in Section IV.C. However, our algorithm can yield more accurate results because it evaluates a global solution for a convex energy function which takes into account both the locally weighted averages and variances.

Fig. 3 demonstrates the comparison results for five SAR images using our algorithm, RSF model, and GMACM method. The experiment is related to the ENVISAT SAR data collected on August 16, 2007, at 01:16 UTC, August 15, 2007, at 13:04 UTC in Peter the Great Bay, on January 09, 2008, at 01:11 UTC on the Korean coast in the Yellow/West Sea. These images contain severe noise and the boundaries of oil slick regions are very weak. The first row shows that our algorithm can yield smooth and continuous boundaries of oil slick regions. The second row shows segmentation results by RSF model which...
contains many small detected regions that do not belong to oil slick regions. This phenomenon illustrates that the RSF model is sensitive to the noise which makes it easy to fall into local minima, leading to yield many false alarms. The third row shows results of GMACM method. Although the results are visually better than RSF model, there still exist many false alarms which affect the following classification. In general, our algorithm achieves the best performance with less number of detected regions and much smoother detected boundaries than RSF model and GMACM method, which facilitate the following classification task.

This experiment of Fig. 4 is related to the ENVISAT C-band SAR data collected on May 21, 2010, at 03:53:53 UTC, May 18, 2010, at 03:48:35 UTC, May 12, 2010, at 15:55:02 UTC, May 09, 2010, at 15:48:22 UTC, in Gulf of Mexico. These images contain severe noise and the boundaries of the oil slick regions are also very blur. Moreover, the intensities of these images are severely inhomogeneous. These factors make reducing misclassification a very challenging task for the region-based methods. The final segmentation results of our method [see Fig. 4(a)] are much more accurate than the RSF model [see Fig. 4(b)] and the GMACM method [see Fig. 4(c)] because of the consideration of local means and variances in the object regions and the background regions in our algorithm. Moreover, because the objective functions of RSF model and GMACM method are non-convex with respect to the level set functions, the final results are easily affected by the severe noise, leading the contours to fall into local minima. However, our algorithm can alleviate this problem because our objective function is convex with respect to all its parameters.

Fig. 5 shows the running time by our algorithm, GMACM and RSF method for 16 SAR oil slick images used in Figs. 3 and 4. we improve the separation accuracy by pursuing the segmentation on the transformed domain and combining the information of the neighboring pixels belonging to the same class. On the other hand, we present a new energy function, which is convex with respect to the level set function, making segmentation results very robust to the initialization of the level set function, facilitating automatic application in a practical system. Comparisons with two representative state-of-the-art active contour models (i.e., RSF model [18] and GMACM method [9]) for oil slick segmentation on several challenging SAR images, confirmed the robustness of the proposed algorithm to the level set initialization and the segmentation accuracy of the proposed algorithm in separating oil slick region and look-alikes.

VI. CONCLUSION

In this paper, we proposed a novel globally statistical active contour model (GSACM) to segment oil slick from SAR images. The proposed model can solve the severe noise, local minima of the energy function, blur boundary and intensity in-homogeneity existing in oil spill SAR images. On the one hand,

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**REFERENCES**


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