SAR SEA ICE IMAGE SEGMENTATION USING AN EDGE-PRESERVING REGION-BASED MRF

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ABSTRACT

In this paper, we propose a novel edge-preserving region (EPR)-based representation for synthetic aperture radar (SAR) images, which is incorporated with a region-level Markov random field (MRF) model to offer an efficient approach to the segmentation of SAR sea ice images. The EPR-based representations of SAR images are constructed by applying the speckle reduction anisotropic diffusion (SRAD) algorithm and the watershed transform, which aims at suppressing oversegmentation within objects while accurately locating object edges at region boundaries in the presence of speckle noise. In combination with a region-level MRF, the EPR-based representation largely reduces the search space of optimization process and improves parameter estimation of feature model, leading to considerable computational savings and less probability of false segmentation. Relative to the existing region-level MRF-based methods, testing results have demonstrated that the proposed method achieves more than 50% reduction of computational time and improves the segmentation accuracy especially at high speckle noise.

Index Terms—Synthetic aperture radar (SAR), image segmentation, Markov random field (MRF), watershed

1. INTRODUCTION

Sea ice information is essential to the safety and efficiency of ship navigation in ice-infested regions. Spaceborne synthetic aperture radar (SAR), such as that carried by the Canadian satellite RADARSAT-1/2, provides an efficient method to monitor sea ice conditions. Manual processing of the large amount of SAR images is labor intensive and time consuming, while the labeling results by ice analysts have limited resolution and accuracy. The use of automated computer vision techniques is hence a desirable means to SAR sea ice image interpretation.

MRF model [1] is capable of characterizing image structure by modeling contextual dependences in images. Under the Bayesian framework, the MRF context model can be combined with a feature model to form a maximum a posteriori (MAP)-MRF framework, offering a mathematically sound way to deal with image segmentation problem. The usefulness of MRF model for SAR sea ice image segmentation has been demonstrated in a number of applications [2-4], while the model still suffers difficulties in seeking accurate segmentation results in a computationally efficient manner. The MRF model at pixel-level is extremely time consuming and prone to be trapped in local minima due to the huge search space. To alleviate the problem, the MRF model can be alternatively applied to primitive homogeneous regions of SAR images obtained by an initial segmentation process [3]. However, the existing region-based representations [3-5] normally have a large number of redundant segments due to speckle noise and intra-object variations, posing obstacles to region-level MRF-based segmentation with respect to both accuracy and computational efficiency.

In this paper, we propose a novel edge-preserving region (EPR)-based representation for SAR images, which is incorporated with the region-level MRF model to offer an efficient approach to the segmentation of SAR sea ice images. The EPR-based representation gives an initial segmentation of SAR images in the form of primitive regions, aiming at the goal of efficiently suppressing oversegmentation within objects while accurately locating object edges at region boundaries. To achieve this goal, object edges and intra-object homogeneity in SAR images are first restored by using the speckle reduction anisotropic diffusion (SRAD) algorithm [6], followed by the watershed transform [7] to reveal local image structure in a region form. By applying the region-level MRF on the EPR-based representation, the much reduced search space greatly accelerates the segmentation process. Moreover, the segmentation accuracy is improved as the result of a more accurate estimate of feature model parameters as well as a more precise location of object boundaries.

In the next section, region-level MRF-based image segmentation is briefly described. Generation of the EPR-based representation of SAR images is then presented in Section 3, followed by evaluations of the proposed method in Section 4. This paper is concluded in Section 5.

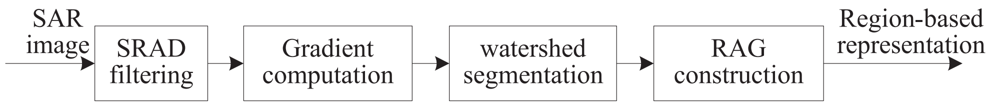


Figure 1. Generation of the EPR-based representation for a SAR image

2. IMAGE SEGMENTATION BASED ON REGION-LEVEL MRF MODEL

Under the Bayesian framework, image segmentation problem can be formulated as a MAP estimate [1]

$$C^* = \arg\max_C P(C|f) = \arg\max_C p(f|C)P(C) \tag{1}$$

where $P(C|f)$ denotes the posterior probability of the segmentation label configuration C given the image feature f, $p(f|C)$ is the conditional probability distribution given the configuration C, referred to as the feature model, and $P(C)$ is the prior probability of the configuration C, referred to as the spatial context model.

Instead of the traditional pixel-level definition, the spatial context model can be applied to constituent regions of images for characterizing pixel interactions in a larger extent. Assuming the feature model follows a Gaussian distribution and the spatial context model takes a multi-level logistic (MLL) MRF model [1] over image regions, the MAP-MRF solution to image segmentation can be obtained by minimizing an objective function as follows:

$$\arg\min_{\{c_r, r\in S\}} \left\{ \sum_{r\in S} \sum_{s\in r} \left\{ \frac{1}{2}\log\left(2\pi\sigma_{c_r}^2\right) + \frac{\left(f_s - \mu_{c_r}\right)^2}{2\sigma_{c_r}^2} \right\} + \alpha \sum_{\langle r,k\rangle \in Q_R} U(c_r, c_k) \right\} \tag{2}$$

where r denotes a region of pixels and the disjoint union of r constitute the image S. c_r denotes the class label of region r, taking a value from the class label set $\{1,\ldots,n\}$ where n is the number of class labels in the segmented image and assumed to be known a priori. f_s denotes image intensity at site s. $\left(\mu_{c_r}, \sigma_{c_r}^2\right)$ denote the mean and variance of pixel intensity of class c_r respectively. α is a weighting parameter balancing the contributions of the feature and spatial context models. $<r, k>$ denotes one pair-region clique of the neighboring regions s and k, and Q_R denotes the set of all pair-region cliques on S. $U(c_r,c_k)$ is the pair-region clique energy defined as:

$$U(c_s, c_k) = \begin{cases} 1 & if \quad c_s \neq c_k \\ 0 & otherwise \end{cases}. \tag{3}$$

3. THE EDGE-PRESERVING REGION (EPR)-BASED REPRESENTATION OF SAR IMAGES

In region-level MRF approach to SAR image segmentation, the performance is closely related to the underlying region-based representation which is expected to have the following two properties. First, object edges are accurately located at region boundaries. Second, oversegmentation within homogeneous objects is as less as possible. These expectations are not well fulfilled in the existing region-based representations [3-5], which are normally generated by applying the watershed transform to SAR images while the characteristics of SAR images are not taken into account. To achieve the desired properties, we propose to introduce an appropriate speckle reduction filtering into the initial segmentation process, leading to so-called edge-preserving region (EPR)-based representations for SAR images.

Generation of the EPR-based representations is generated as illustrated in Fig. 1. The edge-oriented SRAD filtering is first applied to the SAR image for suppressing speckle noise and intra-object variations, generating a piecewise smooth representation where object edges are identified as discontinuities. Based on gradient magnitude of the piecewise smooth representation, the watershed transform is then used to decompose the image into primitive regions, upon which a region adjacency graph (RAG) is constructed to form a region-based representation.

3.1. The SRAD Filter

The SRAD algorithm provides a partial differential equation (PDE) approach to speckle reduction of SAR images by introducing anisotropic diffusion [6] into conventional adaptive speckle filters.

Let I_0 denote the intensity of a SAR image. Starting from I_0, the SRAD algorithm iteratively updates filtering result $I(t)$ according to the following PDE:

$$\begin{cases} \dfrac{\partial I(t)}{\partial t} = div\left[c(q)\nabla I(t)\right] \\ I(0) = I_0 \end{cases} \tag{4}$$

where t is the time variable, div the divergence operator, ∇ the gradient operator. $c(q)$ is the diffusion coefficient

$$c(q) = \frac{1}{1 + \dfrac{q^2 - q_0^2}{q_0^2\left(1 + q_0^2\right)}}, \tag{5}$$

here q is termed instantaneous coefficient of variation defined as

$$q = \left\{ \frac{\frac{1}{2}\left(\frac{\nabla I}{I}\right)^2 + \frac{1}{16}\left(\frac{\nabla^2 I}{I}\right)^2}{\left[1+\frac{1}{4}\left(\frac{\nabla^2 I}{I}\right)\right]^2} \right\}^{1/2} . \quad (6)$$

q_0 is a parameter controlling the degree of smoothing which can be determined by

$$q_0 = \frac{\sigma(I(t))}{\mu(I(t))} \quad (7)$$

where $\mu(I(t))$ and $\sigma(I(t))$ are the mean and standard deviation of $I(t)$ over a homogeneous region respectively.

3.2. Initial Segmentation Using Watershed Transform

The watershed algorithm [7] is a popular morphological tool for image segmentation. It uses a drainage pattern of simulated rainfall to partition an image into disjoint regions called catchment basins separated by watershed lines. Based on the gradient magnitudes of an image, the watershed algorithm combines identification of discontinuities and a region growing technique to reveal topological structure of the image, which detects object edges at boundaries of watershed regions.

In this work, based on gradient magnitudes of the SRAD filtering result, we adopt immersion simulations algorithm [7] to compute watersheds of a SAR image. To facilitate the use of the MRF model on region level, a region adjacency graph (RAG) [1] is then constructed to represent the watershed regions and their context relationships in the segmented image.

4. SEGMENTATION TESTING AND RESULTS

SAR sea ice image segmentation using the region-level MRF model upon the proposed EPR-based representation is tested on a synthetic SAR image corrupted with varying level of speckle noise and a real SAR image. The proposed method is also compared to two other segmentation methods: 1) the region-level MRF model upon noisy region (NR)-based representation, which is a RAG representation of the watershed segmentation of SAR images, 2) the traditional pixel-level MRF model.

Method performance is evaluated in terms of the computational time and segmentation accuracy. Overall accuracy and kappa are used to measure segmentation accuracy. Overall accuracy refers to the percentage of pixels correctly labeled while kappa measures the performance in terms of the classification agreement.

4.1. Synthetic Image Segmentation

The segmentation method is first evaluated using a synthetic image shown in Fig. 2. This 512×512 image consists of a star as well as bars and curves each with different widths. The image is corrupted by multiplying simulated speckle noise at eight levels with the corresponding number of looks (L): 50, 30, 25, 20, 15, 10, 5, 1.

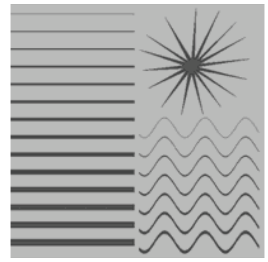


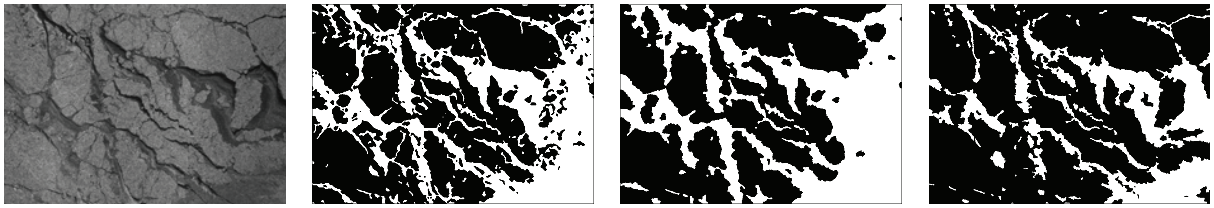
Figure 2. A synthetic image.

Table I. Segmentation results (overall accuracy / kappa) for Fig. 2 corrupted with speckle noise.

L	Pixel-level MRF	Region-level MRF upon	
		the NR-based representation	the EPR-based representation
50	99.9/0.998	99.8/0.994	99.8/0.995
30	99.8/0.992	99.7/0.988	99.7/0.990
25	99.7/0.989	99.5/0.983	99.6/0.986
20	99.5/0.981	99.4/0.977	99.5/0.982
15	99.3/0.974	99.2/0.969	99.3/0.974
10	Fail	98.6/0.945	98.9/0.959
5	Fail	96.9/0.883	98.0/0.923
1	Fail	Fail	93.3/0.728

Fail means the optimization process fails to converge to a two-class segmentation result

Table I lists the segmentation accuracy of the synthetic image (Fig. 2) across different speckle noise levels. When the speckle noise level is relatively low, with L greater than 15, the pixel-level MRF obtains better segmentation accuracy than the region-level MRF on NR-based representation. The latter suffers false segmentation due to deviations between the object edges and region boundaries. While at the increasing noise level, the pixel-level MRF fails to converge to a two-class segmentation result since the speckle noise causes the estimates of feature model parameters seriously deviate from their true values. Upon the NR-based representation instead of pixels of SAR images, the impact of speckle noise on parameter estimation is reduced, while the difficulty with convergence still remains when the noise level goes up to 1-look. In contrast, the region-level MRF on the EPR-based representation achieves more accurate segmentation results than the pixel-level MRF at noise levels of L less than 25, and is superior to the region-level MRF on the NR-based representation across all speckle noise levels.



(a) Original SAR image

(b) Segmentation using pixel-level MRF

(c) Segmentation using region-level MRF upon the NR-based representation.

(d) Segmentation using region-level MRF upon the EPR-based representation.

Figure 3. Segmentation of a SAR image captured over Beaufort sea

Compared to the NR-based representation, the EPR-based representation has a much less number of regions with an average reduction ratio of 78%, indicating considerable computational savings. The segmentation algorithms are implemented with C++ and run on a PC with 3GHz Pentium CPU and 2GB memory. The average computational time for the segmentation of Fig. 2 corrupted with speckle noise using the pixel-level MRF is 75 seconds while only 17 seconds are needed by the region-level MRF upon the NR-based representation. By using the EPR-based representation, the computational time is further reduced to 8 seconds, saving more than half the time.

4.2. SAR Sea Ice Image Segmentation

The proposed method is also evaluated using a SAR sea ice image shown in Fig. 3a, which is captured by RADARSAT-1 in ScanSAR C-band mode at the resolution of 100m (2×2 block average of original images at 50m resolution). In this image, the brighter area is *multi-year ice* and the rest is *grey-white ice*.

Fig. 3b gives the segmentation results using the pixel-level MRF. Most of the grey-white ice in the right of the image is falsely segmented into the multi-year ice. As shown in Fig. 3c, the false segmentation still remains in the segmentation result using the region-level MRF on the NR-based representation. A large improvement of the segmentation can be seen in Fig. 3d, where the use of the proposed EPR-based representation leads to a successful separation between the grey-white ice and the multi-year ice.

With respect to the computational time, the pixel-level MRF takes 390 seconds while the region-level MRF upon the NR-based representation needs 61 seconds. In contrast, only 27 seconds are used by the EPR-based representation.

5. CONCLUSIONS

In this paper, an efficient method for the segmentation of SAR sea ice imagery is proposed by combining the region-level MRF model and a new EPR-based representation. Relative to the existing region-based representation, the proposed EPR-based representation largely reduces oversegmentation while has less deviations between object edges and region boundaries, improving the region-level MRF approach to SAR image segmentation with respect to both computational efficiency and accuracy. The proposed method can also be applied to the segmentation of generic SAR images.

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