SEC: Stochastic ensemble consensus approach to unsupervised SAR sea-ice segmentation

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Abstract

The use of synthetic aperture radar (SAR) has become an integral part of sea-ice monitoring and analysis in the polar regions. An important task in sea-ice analysis is to segment SAR sea-ice imagery based on the underlying ice type, which is a challenging task to perform automatically due to various imaging and environmental conditions. A novel stochastic ensemble consensus approach to sea-ice segmentation (SEC) is presented to tackle this challenging task. In SEC, each pixel in the SAR sea-ice image is assigned an initial sub-class based on its tonal characteristics. Ensembles of random samples are generated from a random field representing the SAR sea-ice imagery. The generated ensembles are then used to re-estimate the sub-class of the pixels using a weighted median consensus strategy. Based on the probability distribution of the sub-classes, an expectation maximization (EM) approach is utilized to estimate the final class likelihoods using a Gaussian mixture model (GMM). Finally, maximum likelihood (ML) classification is performed to estimate the final class of each pixel within the SAR sea-ice imagery based on the estimated GMM and the assigned sub-classes. SEC was tested using a variety of operational RADARSAT-1 and RADARSAT-2 SAR sea-ice imagery provided by the Canadian Ice Service (CIS) and was shown to produce successfully segmentation results that were superior to approaches based on K-means clustering, Gamma mixture models, and Markov Random Field (MRF) models for sea-ice segmentation.

1. Introduction

The monitoring of sea ice conditions in polar regions is important for various purposes such as climate research and ship routing. An effective tool for monitoring sea ice conditions is the use of spaceborne synthetic aperture radar (SAR) imagery acquired through satellites such as RADARSAT-1/2. One of the key advantages of using SAR for the purpose of sea-ice monitoring is that, by operating in the microwave range, data can be acquired at different times and under different weather conditions (e.g., cloud cover and snow). As such, SAR allows sea-ice conditions to be monitored daily with little interruption. Traditionally, to analyze sea ice conditions using SAR imagery, trained experts were required to manually segment and classify sea-ice imagery to create daily sea-ice charts, which is very time consuming and laborious. Furthermore, the results had limited accuracy as it is not possible for trained experts to perform the analysis on a pixel level. As such, automated approaches for segmenting sea-ice images is desired to help in the sea-ice analysis process.

The task of segmenting SAR sea-ice imagery is a difficult challenge for a number of reasons. First, complex factors such as SAR backscatter and environmental conditions result in image inhomogeneities throughout the SAR imagery. Second, due to signal characteristics, SAR imagery is highly contaminated by speckle noise. Consequently, extracting reliable tonal and texture characteristics from SAR imagery for segmentation purposes is a difficult task. An example of this difficulty is illustrated in Fig. 1, where a SAR sea-ice image acquired using RADARSAT-1 and its corresponding tonal probability distribution is shown. Typical to SAR imagery, the tonal probability distribution if the SAR sea-ice image is unimodal in nature, thus making it very challenging to perform segmentation based on tonal characteristics in a direct manner.

Automated approaches for SAR sea-ice image segmentation can be generally categorized into two main groups: i) global segmentation methods, and ii) local segmentation methods. In global segmentation methods [1, 2, 3, 4], the SAR sea-ice image is segmented into regions based on the tonal probability distribution of the entire SAR sea-ice image. Different approaches for segmenting the im-

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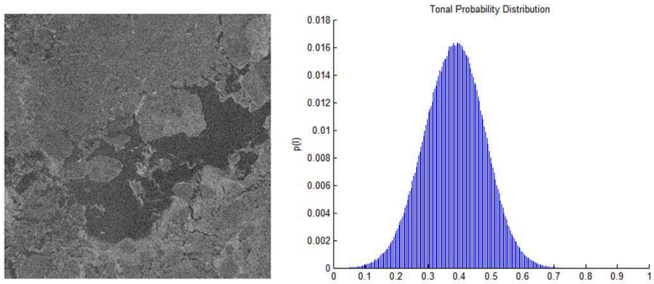

(a) (b)

Figure 1. (a) RADARSAT-2 image. (b) Tonal probability distribution.

ages based on tonal probability distributions include local thresholding [1], Gamma mixture models [2], K-means clustering [3], and Gaussian mixture models [4]. By exploiting global tonal characteristics from the entire image, global segmentation methods are less prone to over-segmentation and under-segmentation issues when compared to local segmentation methods. Unfortunately, since global segmentation methods ignore spatial relationships between pixels, they are highly sensitive to image noise. While filtering methods exist for reducing the effects of speckle noise [5, 6, 7], these methods perform poorly under high speckle noise contamination. Given the high level of speckle noise contamination in SAR sea-ice imagery, such global segmentation methods are not well suited for operational purposes.

In local segmentation methods [8, 9, 10, 11], segmentation is performed based on the local spatial and tonal relationships between pixels in the SAR sea-ice image. Different approaches to segmenting the images based on local spatial, tonal, and texture relationships include Markov Random Field (MRF) clustering [8], pixel-based region growing [9, 10], and region-based region growing [11] based on a Markov Random Field (MRF) spatial context model. By exploiting local spatial relationships, local segmentation methods are more robust to the effects of speckle noise when compared with global segmentation methods. Given the high level of speckle noise contamination in SAR sea-ice imagery, this is very critical to achieving accurate segmentation results. Unfortunately, as only local information is utilized, local segmentation methods are more prune to over-segmentation and under-segmentation issues when compared to global methods depending on the imaging conditions. The underlying goal of the proposed method is to combine the advantages of both global and local segmentation approaches to address the aforementioned issues.

The main contribution of this paper is a novel stochastic ensemble consensus (SEC) approach for the segmentation of SAR sea-ice imagery. By utilizing both global and local tonal and spatial characteristics to perform image segmentation in a stochastic manner, the SEC method aims to alleviate the effects of high speckle noise contamination faced by global methods, as well as reduce over-segmentation and under-segmentation issues faced by local methods. This paper is organized as follows. The theory underlying the SEC segmentation method is presented in Section 2. The SEC segmentation method as applied to sea-ice imagery is described in detail in Section 3. Experimental results as applied to operational RADARSAT-1 and RADARSAT-2 SAR sea-ice imagery provided by the Canadian Ice Service (CIS) are presented and discussed in Section 4. Finally, conclusions are drawn and future work is discussed in Section 5.

2. Theory

2.1 Problem Formulation

Let S be the discrete lattice upon which SAR sea-ice imagery is defined and $s \in S$ be a site in the lattice. Let L_s be a random variable taking on a class $\{1, ..., n\}$ to which s belongs, and F_s be a random variable taking on the observed intensity (tonal value) associated with s. Given a SAR sea-ice image f, let $f = \{f_s | s \in S\}$ be all tonal values on S and $l = \{l_s | s \in S\}$ be all class labels on S. Therefore, the problem of SAR sea-ice segmentation is essentially an inverse problem, where we wish to determine l given f. This can be formulated as the following maximization problem,

$$\hat{l} = \arg\max_{l} \{P(l\,|f)\}\,, \tag{1}$$

where $P(l|f)$ is a posteriori knowledge.

2.2 Stochastic Ensemble Consensus

As discussed in Section 1, global and local SAR sea-ice segmentation methods have unique advantages that are complementary to each other. While global segmentation methods are less prone to over-segmentation and under-segmentation issues by exploiting global tonal characteristics, local segmentation methods provide greater robustness to the effects of speckle noise. Intuitively, a hybrid segmentation approach that exhibits the advantages of the global and local segmentation methods is desired. In order to design such an approach, to understand the principles behind each class of image segmentation methods is important . One approach to visualizing and understanding the two classes of SAR image segmentation approaches is to formulate the segmentation strategies in a novel manner based on the concept of consensus decision-making. Consensus decision-making is a group decision-making concept where the underlying goal is to achieve general agreement amongst the participants in the group with regards to the final decision. In both local and global segmentation approaches, the class label l associated with site s is determined based on the consensus amongst an ensemble of other sites in the image $T = \{t_1, t_2, \ldots, t_N | T \subseteq S\}$, as determined by a consensus function $C_s(t_1, t_2, \ldots, t_N)$. The key difference between the local and global segmentation approaches is in the construction of ensembles of sites used for the consensus decision making process. In local approaches, the neighboring sites of s are chosen to form the ensemble for estimating l_s to enforce spatial locality in the consensus decision-making process. As such, consensus is achieved based purely on local spatial interactions amongst neighboring sites. This approach to consensus decision-making exploits the fact that sites that are close to each other are more likely to belong to the same class, and hence is effective in suppressing the effect of noise on the segmentation results. In global approaches, the ensemble used in the consensus decision-making process for estimating l_s consists of all possible sites in the image,

$$T = \{\forall s \in S\}. \tag{2}$$

As such, consensus is achieved based on the tonal characteristics of the entire image, thus exploiting a greater quantity of information to alleviate issues associated with over-segmentation and under-segmentation issues faced by local methods due to limited information. In both classes of segmentation approaches, the consensus function $C_s(t_1, t_2, \ldots, t_N)$ is generally based purely on the individual tonal values at each site in the ensemble $\{f_{t_1}, f_{t_2}, \ldots, f_{t_N}\}$.

Based on the aforementioned consensus decision-making view of the two classes of image segmentation approaches, one approach to combining the advantages of global and local segmentation methods is to account for local spatial interactions in the consensus function $C_s(t_1, t_2, \ldots, t_N)$ rather than in the ensemble construction process. By shifting the spatial locality constraint from the ensemble construction process to the consensus decision-making process, all possible sites in the image can now be utilized in the ensemble used for estimating l_s, as in the case of global approaches, while still accounting for local spatial relationships as in the case of local approaches. As such, this hybrid approach utilizes global information to alleviate issues associated with over-segmentation and under-segmentation, while reducing the effects of speckle noise by taking local spatial relationships into account.

There are two main issues that need to be addressed in the aforementioned hybrid approach. The first issue associated with the hybrid approach is in the design of a consensus function $C_s(t_1, t_2, \ldots, t_N)$ that takes into account local spatial relationships in estimating l_s. One approach to formulating a consensus function that accounts for local spatial relationships is to weight the influence of a particular site t_i on the estimation of l_s based on the similarity between the local neighborhoods $\aleph_s$ and $\aleph_{t_i}$ around s and t_i respectively, where the influence Ψ of a site on the consensus decision-making process is inversely proportional to the dissimilarity between the local neighborhood configurations,

$$\Psi_s(t_i) \propto \frac{1}{\|f_{\aleph_s} - f_{\aleph_{t_i}}\|}. \tag{3}$$

where $f_{\aleph_s}$ and $f_{\aleph_{t_i}}$ represent the set of tonal values associated with local neighborhoods $\aleph_s$ and $\aleph_{t_i}$ respectively. This influence weighting scheme is based on the intuition that sites that have similar local neighborhood configurations are more likely to belong to the same class.

The second issue associated with the hybrid approach is in the computational cost associated with using all possible sites in the image in the ensemble used for estimating l_s, which can be computationally expensive for large images such as SAR sea-ice imagery due to the increased complexity of accounting for local spatial relationships in the consensus function. To significantly reduce the computational overhead associated with the consensus decision-making process, we propose that the ensemble be constructed in a stochastic manner, consisting of random sites instead of all possible sites within the image. This stochastic ensemble approach allows for a good approximation of the desired solution while significantly reducing the computational overhead of the segmentation method.

3 SEC Segmentation Method

Based on the theory presented in Section 2, the stochastic ensemble consensus (SEC) segmentation method can be described as follows. Let K_s be a random variable taking on a sub-class $\{1, ..., m \mid m > n\}$ to which s belongs to and $k = \{k_s | s \in S\}$ be all sub-class labels on S. For a SAR sea-ice image f, where the tonal values are within the range of (0,1), let each site s be assigned an initial sub-class label k_s, where k_s was determined as follows,

$$k_s = round\left[f_s m\right] \tag{4}$$

Based on empirical testing, a suitable number of sub-classes is kept constant at $m = 150$. For a given site s, a set of N random sites $T = \{t_1, t_2, \ldots, t_N\}$ are generated from S to form the ensemble used to estimate l_s based on a spatially-adaptive probability density function p,

$$p(t|s) = \frac{1}{|t - s|^{\gamma}}, \tag{5}$$

where γ is the sampling density decay factor. Based on empirical testing, a suitable decay factor is kept constant at

$\gamma = 0.3$. This spatially-adaptive sampling approach reintroduces the influence of spatial locality into the ensemble construction process while still exploiting global tonal characteristics within the image.

Given the ensemble of random sites $T = \{t_1, t_2, \ldots, t_N\}$, the influence $\Psi_s(t_i)$ of a site t_i on the consensus decision-making process of s can be computed as scaled exponential of the negative cumulative Geman-McClure [12] tonal distance between the respective local neighborhoods $\aleph_{t_i}$ and $\aleph_s$

$$\Psi_s(t_i) = round\left(\alpha \exp\left[-\sum \frac{(f_{\aleph_s} - f_{\aleph_{t_i}})^2}{\left(1 + (f_{\aleph_s} - f_{\aleph_{t_i}})^2\right)\omega}\right]\right), \tag{6}$$

where α and ω are the scaling and influence decay constants respectively. Based on empirical testing, suitable constants are kept at $\alpha = 20$ and $\omega = 0.4$. Based on the influence $\Psi_s(t_i)$, the sub-class label k_s is re-estimated based on the ensemble of random sites $T = \{t_1, t_2, \ldots, t_N\}$ using an influence-weighted median consensus strategy,

$$\hat{k}_s = C_s(t_1, t_2, \ldots, t_N) = median\left[\Psi_s(t_i) \diamond k_{t_i}|_{i=1}^{N}\right], \tag{7}$$

where $\diamond$ is the replication operator defined as $a \diamond b = \overbrace{b, b, \ldots, b}^{a \text{ times}}$. This consensus strategy allows the influence of each site on the consensus decision-making process to vary according to the similarity of its local neighborhood configuration to that of s.

The objective of the aforementioned stochastic ensemble consensus decision-making process for re-estimating k_s is to re-label each site in the image such that there is general agreement among the sites in the ensemble as to what the sub-class of s should be. As such, sites that have similar local neighborhood configurations should intuitively cluster together towards a common sub-class label. To validate this intuition, the sub-class probability distribution $p(k)$ of the SAR sea-ice image from Fig. 1 after the proposed stochastic ensemble consensus decision-making process is shown in Fig. 2. Unlike the tonal probability distribution shown in Fig. 1, the sub-class probability distribution $p(k)$ follows a multimodal distribution and as such a purely global segmentation approach can be used to determine the final class label l_s based on the sub-class probability distribution of the entire SAR sea-ice image. In the SEC method, a n-class Gaussian mixture model (GMM) for final class likelihoods is first estimated based on the sub-class labels k of all v sites in the image,

$$p(\mathbf{k}|l = i, \theta) = \mathcal{N}(\mu_i, \sigma_i), \tag{8}$$

where θ are the unknown parameters of the GMM,

$$\theta = \{\mu_1, \ldots, \mu_n, \sigma_1, \ldots, \sigma_n, P(k = 1), \ldots, P(k = n)\}. \tag{9}$$

The estimation of θ is performed using expectation-maximization [13],

$$\theta_{t+1} = \arg\max_{\theta} \sum_{j=1}^{v} \sum_{i=1}^{n} p\left(l_j = i|\mathbf{k}_j, \theta_t\right) \ln p\left(l_j = i, \mathbf{k}_j|\theta\right), \tag{10}$$

where,

$$p(l_j = i|\mathbf{k}_j, \theta_t) = \frac{p(\mathbf{k}_j|l_j = i, \theta_t)p(l_j = i|\theta_t)}{\sum_{u=1}^{n} p(\mathbf{k}_j|l_j = u, \theta_t)p(l_j = u|\theta_t)}. \tag{11}$$

Finally, based on the estimated GMM of final class likelihoods, the maximum likelihood (ML) estimate of the final class l_s of site s can then be determined as

$$\hat{l}_s = \arg\max_{l} p(k_s|l). \tag{12}$$

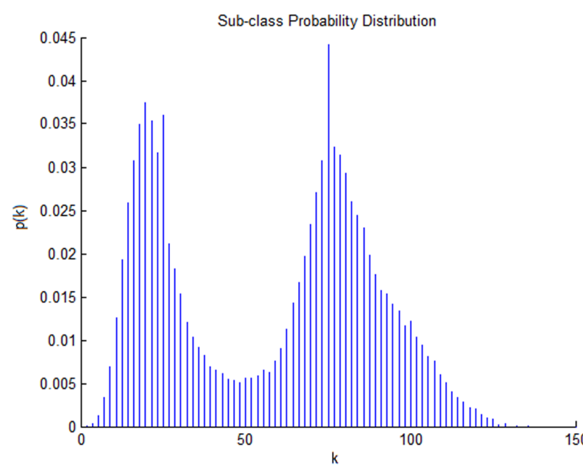

Figure 2. Sub-class probability distribution $p(k)$ of the RADARSAT-2 image from Fig. 1. Unlike the tonal probability distribution of the image, the sub-class probability distribution $p(k)$ follows a multimodal distribution and as such a purely global segmentation approach can be used to determine the final class label l_s based on $p(k)$.

4. Experimental Results

The proposed SEC SAR sea-ice segmentation method was tested using three SAR sea-ice images provided by the Canadian Sea Ice Service (CIS). The SAR sea-ice images under test can be described as follows:

Test 1: RADARSAT-1, C-band HH, 100m pixel spacing.
Test 2: RADARSAT-2, C-band HV, 50m pixel spacing.
Test 3: RADARSAT-2, C-band HV, 50m pixel spacing.
Test 4: RADARSAT-2, C-band HH, 50m pixel spacing.

All of the tested images are highly contaminated by speckle noise, making it difficult to segment even manually by trained human experts. Furthermore, the tonal probability distributions of all test images are unimodal, thus making it very challenging to perform segmentation based on tonal characteristics in a direct manner. For comparison purposes, segmentation using K-means clustering (like that proposed in [3]), segmentation using Gamma mixture models (like that proposed in [2]), and segmentation using a Markov Random Field (MRF) model (like that proposed in [8]) was also performed on each test set.

The segmentation results of the test images are shown in Fig. 3, Fig. 4, Fig. 5, and Fig. 6. The segmentation results produced using K-means clustering and Gamma mixture models, both global segmentation methods, show that while the boundaries of ice floes and leads are visible, the segmentation of regions is very noisy since local spatial relationships are not accounted for. The segmentation results produced using the MRF model are significantly less noisy, since they account for local spatial relationships, but much of the detail in the original imagery such as leads and fine floe boundaries are lost. The segmentation results produced by the proposed SEC method are also significantly less noisy than that produced using K-means clustering and Gamma mixture models, but is also able to maintain detail in the original imagery such as leads and fine floe boundaries better than the MRF model. This demonstrates the effectiveness of the SEC method in providing accurate segmentation for SAR sea-ice imagery by combining the advantages of both local and global segmentation approaches.

5. Conclusions

In this paper, a novel stochastic ensemble consensus approach to sea-ice segmentation (SEC) is proposed for the purpose of SAR sea-ice image segmentation. An adaptive stochastic approach to constructing ensembles of random sites for consensus decision-making based class estimation is introduced. An influence-weighted median consensus strategy is introduced for sub-class re-estimation of each pixel in the SAR sea-ice image. An expectation maximization approach is presented for estimating the final class likelihoods based on the sub-class probability distribution, with which the final class of each pixel in the image can be determined using maximum likelihood classification. Experimental results using operational RADARSAT-1 and RADARSAT-2 SAR sea-ice imagery provided by the Canadian Ice Service (CIS) showed that the SEC method provided superior segmentation results when compared with approaches based on K-means clustering, Gamma mixture models, and Markov Random Field (MRF) models. Future work includes the investigation of alternative sampling schemes for the stochastic ensemble construction process, as well as alternative approaches for evaluating the similarity between local neighborhood configurations.

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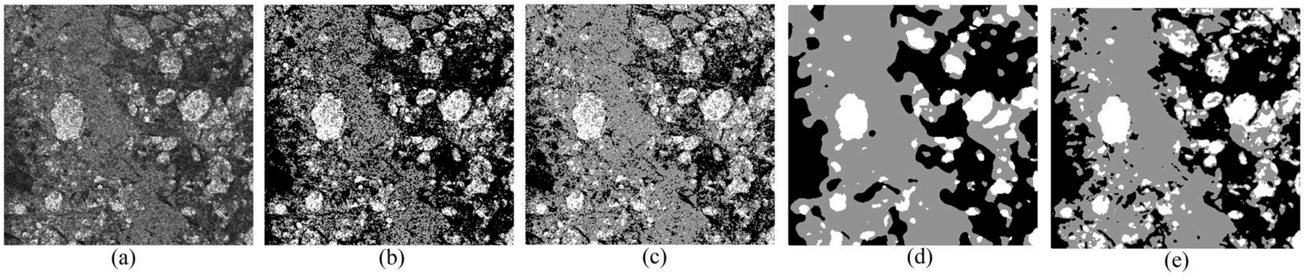

Figure 3. Test 1: (a) Original RADARSAT-1 image. Segmentation using (b) K-means, (c) Gamma mixture model, (d) MRF model, and (e) SEC.

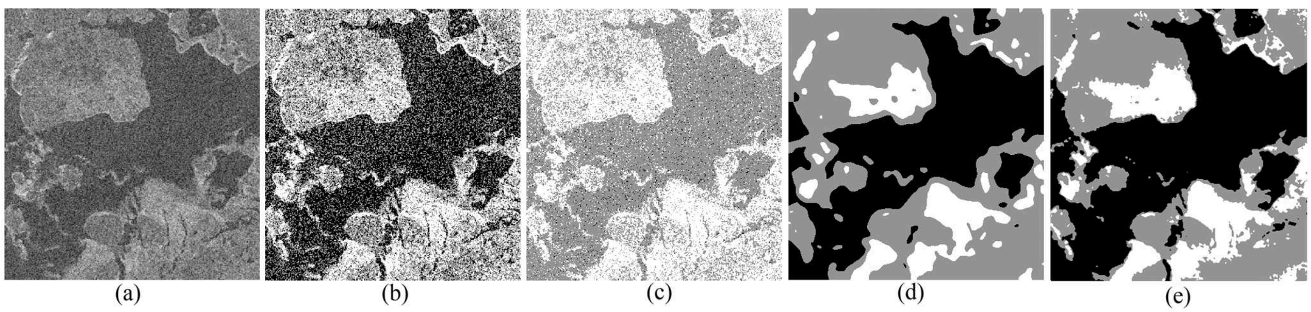

Figure 4. Test 2: (a) Original RADARSAT2 image. Segmentation using (b) K-means, (c) Gamma mixture model, (d) MRF model, and (e) SEC.

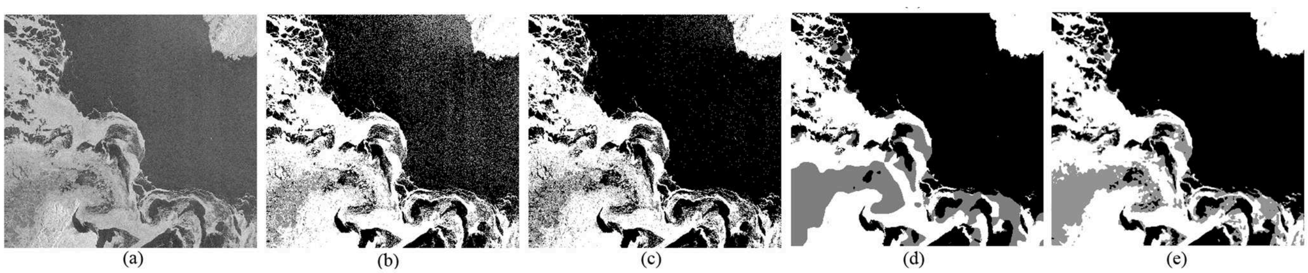

Figure 5. Test 3: (a) Original RADARSAT2 image. Segmentation using (b) K-means, (c) Gamma mixture model, (d) MRF model, and (e) SEC.

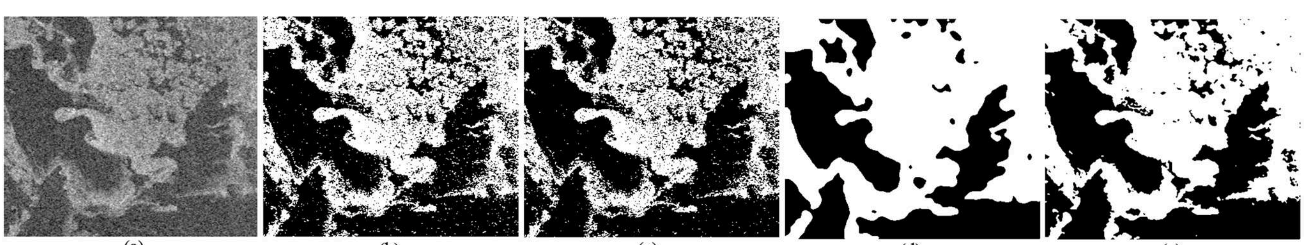

Figure 6. Test 4: (a) Original RADARSAT2 image. Segmentation using (b) K-means, (c) Gamma mixture model, (d) MRF model, and (e) SEC.

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