Unsupervised Segmentation of Synthetic Aperture Radar Sea Ice Imagery Using MRF Models

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Abstract

Due to both environmental and sensor reasons, it is challenging to develop computer-assisted algorithms to segment SAR (synthetic aperture radar) sea ice imagery. In this research, images containing either ice and water or multiple ice classes are segmented. This paper proposes to use the image intensity to discriminate ice from water and to use texture features to separate different ice types. In order to seamlessly combine spatial relationship information in an ice image with various image features, a novel Bayesian segmentation approach is developed. Experiments demonstrate that the proposed algorithm is able to segment both types of sea ice images and achieves an improvement over the standard MRF (Markov random field) based method, the finite Gamma mixture model and the K-means clustering method.

Keywords: Image segmentation, unsupervised segmentation, Markov random field (MRF), image feature, expectation-maximization (EM), K-means clustering, Gamma distribution, mixture model, synthetic aperture radar (SAR), sea ice, texture.

1 Introduction

A major research initiative on the polar regions is to obtain timely information on the distribution and dynamics of sea ice [1]. The most important tool is satellite-based synthetic aperture radar (SAR) systems. As an important aspect of measurement, monitoring and understanding of sea ice evolution during the seasons, the generation of ice type maps is a fundamental step in interpretation of these data. Automated segmentation techniques are expected to improve throughput, reduce costs and reduce human bias. Unfortunately, as SAR sea ice imagery is complicated due to the existence of speckle noise [2] and the difficulty in differentiating different ice types [1] [3], no segmentation techniques have been reported to achieve satisfactory results. The operational segmentation of SAR sea ice imagery requires identifying the proportions of specific multiple ice classes for a certain region and coding this information in an "egg code" using the World Meteorological Organization (WMO) standards (http://www.cis.ec.gc.ca/). Our research in the current stage is mainly concerned with segmenting two types of sea ice imagery. One type is images containing ice and water which require to separate ice regions from water regions. Also, images with multiple ice categories must be segmented into different ice classes.

A commonly used strategy for segmenting sea ice images is to first choose a proper set of image features and then apply a segmentation method on the chosen features. For choosing image features, this paper proposes to use image intensity to discriminate ice regions from water regions and to use texture features to separate ice type regions (Section 2). For choosing segmentation methods, the thresholding method has commonly been applied. The algorithm [4] first selects thresholding values from local regions and then thresholds the entire image. As it accounts for the local variance in an image, it meets success in segmenting the sea ice images which have an obviously bimodal gray level distribution. There are some other segmentation methods which have stronger potential to segment SAR sea ice images. The finite Gamma mixture model is originally applied in [5] to estimate proportions of ice types in a SAR image. This method can be further used to segment sea ice images. The K-means clustering method [6] has been widely deployed to segment various images and is also potential to be applied to segment SAR sea ice images. The weakness of the three methods above is that they ignore spatial relationship information among image pixels and it is difficult to integrate the spatial relationship information into them. The segmentation results achieved by these methods are often sensitive to image noise and hence inappropriate for operational purposes.

A Markov random field (MRF) is able to account for local spatial relationships [7]. There are various MRF-based segmentation models that have been developed [8] [9]. However, the application of MRF models to segment SAR sea ice imagery has not been commonly represented in the research literature. A standard MRF model is used as a basis for the development here (Section 3). The standard model consists of two components: a region labelling component and a feature modelling component. The region labelling component imposes a homogeneity constraint on the image segmentation process, while the feature modelling component functions to fit the feature data. In the standard approach, a constant weighting parameter is used to combine the two components [8] [9]. This model works very well if training data is available to estimate the parameters of both components. Under the unsupervised environment that is required by operational segmentation of SAR imagery (http://www.cis.ec.gc.ca/), the above model is unable to work consistently. This is caused by the constant weighting parameter [8] [9] (Eq. (5)) which is unable to achieve a proper balance between the two components in the entire segmentation procedure.

A robust implementation scheme proposed in [10] is used in this work to combine the two components by introducing a variable weighting parameter between them (Section 4). The variable parameter first functions as learning approximately globally optimal model parameters. A balance is then achieved between the two components such that the spatial relationship information can be taken into account to refine the model parameters. This approach is demonstrated to eventually generate more accurate segmentation results than the model with a constant weighting parameter (Section 5).

2 Feature Representation

2.1 Image Intensity

Backscatter in SAR sea ice imagery depends on the surface roughness as well as the dielectric constant of sea ice or open water. In theory, backscatter (represented by gray tone) in the SAR imagery plays an important role in visual interpretation of sea ice images. However, algorithms based only on tonal statistics have been demonstrated to have poor separation for different ice types [11]. This poor type separation is primarily caused by gray tone variation which is very common in ice types due to their roughness and the existence of ridges, rubble, rims and deformation [12]. Some success has been met when using variation after filtering [13], but the improvement is marginal [14]. Section 2.2 will discuss the application of texture features to improve classification between sea ice types.

As open water in seas and oceans generally has a larger dielectric constant than the ice-infected regions, most of the incident radar energy is reflected (not backscattered) so that the SAR image in open water areas looks much darker than the ice regions. To partition ice regions from water regions, therefore, the image intensity is strongly advocated. A difficulty in this application is that speckle noise often exists in SAR images, due to that backscattered radar signal has disturbed by the constructive and destructive interference of coherent electromagnetic radiation. The speckle noise can be reduced by using multiple looks or non-coherent integration [2]. The speckle-reduced sea ice image is however not constant-piecewise but generally a Gamma distribution of its pixel values [15]. Denote the site of a pixel in an image by s and the gray value of the pixel s by x_s and the class label of s by y_s. The Gamma distribution of x_s with respect to the mean μ_m of all pixels belonging to the m-th class (ice/water) is [5]:

$$p(x_s|y_s = m) = \frac{l^l}{\mu_m^l (l-1)!} x_s^{l-1} \exp\left(-\frac{l}{\mu_m} x_s\right), \tag{1}$$

where l denotes the number of looks.

2.2 Texture Features

Texture is a very important cue in the human vision system. Texture features have also been proven to be potential for classifying sea ice types in SAR imagery [16] [17] [18]. Various texture methods are available to extract texture features in literatures. For SAR sea ice imagery classification, there is strongly supportive evidence [16] [17] that the gray level co-occurrence probability (GLCP) method [19] is an efficient method to extract texture features which can achieve superior performance than other methods.

Although the GLCP method is hoped to capture consistent feature measurements for the same class regions in an image, the natural inhomogeneity of an ice region and spatial variation in the seasonal measurements will cause variation in the feature response. Generally, the feature response can be modelled by a Gaussian distribution function. Even if the distribution of a feature data is not a Gaussian distribution, the Gaussian function can still be used to

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approximate it since a close unimodal distribution is expected. Denote the feature vector extracted from a random image ($X = x$) by $F = f$, where F denotes a random variable and f is an instance of F. $Y = y$ stands for a segmented result based on the feature vector $F = f$. That is,

$$p(f_s^k|y_s = m) = \frac{1}{\sqrt{2\pi{\sigma_m^k}^2}} \exp\left[-\frac{(f_s^k - \mu_m^k)^2}{2{\sigma_m^k}^2}\right], \quad (2)$$

where μ_m^k and σ_m^k are the mean and standard deviation for the m-th class in the k-th feature component, and f_s^k is the k-th feature component of f at site s.

3 Segmentation Model

The segmentation problem can be expressed in the Bayesian framework. According to the Bayes rule, the segmentation problem is formulated as

$$P(Y = y|F = f) = \frac{p(F = f|Y = y)P(Y = y)}{p(F = f)}. \quad (3)$$

$P(Y = y|F = f)$ is the posteriori probability of $Y = y$ conditioned on $F = f$. $p(F = f|Y = y)$ denotes the probability distribution of $F = f$ conditioned on $Y = y$ and functions to fit the feature data, which is thus referred to as the feature modelling component. $P(Y = y)$ is the a priori probability of $Y = y$ and is used to describe the label distribution of a segmented result only, which is normally referred to as the region labelling component. $p(F = f)$ is the probability distribution of $F = f$.

A few assumptions are required to derive an MRF-based segmentation model. *The first assumption is that each component of $F = f$ be independent on the other components with respect to $Y = y$ (conditional independence).* Suppose there are K components in the feature vector $f = \{f^k|k = 1, 2, \cdots, K\}$. Eq. (3) is then transformed into:

$$P(Y = y|F = f) = \frac{\prod_{k=1}^{K}[p(f^k|Y = y)]P(Y = y)}{p(F = f)}, \quad (4)$$

where $p(f^k|Y = y)$ stands for the probability distribution of the extracted feature component f^k conditioned on the segmented result $Y = y$. As $F = f$ is known and only the relative probability is of concern when maximizing $P(Y = y|F = f)$, $p(F = f)$ does not vary with respect to any solution $Y = y$ and hence the denominator can be disregarded.

Suppose the energy form of $P(Y = y)$ is E_R and that of $\prod_{k=1}^{K}[p(f^k|Y = y)]$ is E_F. A general energy form E for $P(Y = y|F = f)$ can be derived from the product of $P(Y = y)$ and $\prod_{k=1}^{K}[p(f^k|Y = y)]$:

$$E = E_R + \alpha E_F, \quad (5)$$

where α is a weighting parameter to determine how much E_R and E_F individually contribute to the entire energy E.

A concrete form for both E_R and E_F is required for practical segmentation. Most MRF-based segmentation models use the second order pairwise MLL (multi-level logistic) model for modelling the label distribution [7]. The energy of the pairwise MLL model is as follows.

$$E_R(y) = \sum_s \left[\beta \sum_{t \in N_s} \delta(y_s, y_t)\right], \quad (6)$$

where $\delta(y_s, y_t) = -1$ if $y_s = y_t$, $\delta(y_s, y_t) = 1$ if $y_s \neq y_t$, and β is a constant which can be specified a priori [7]. $E_R(y)$ denotes the energy regarding image regions.

The forms of $p(f^k|Y = y)$ may be different regarding what features are used. For the task of partitioning ice regions from water regions, the intensity feature is used as the single image feature. As indicated in Section 2.1, the intensity feature can be modelled using a Gamma distribution. The energy form E_F of Eq. (1) is written as:

$$E_F(x) = \sum_{s, Y_s = m} \left\{\frac{l}{\mu_m} x_s - (l-1)\log x_s + l \log \mu_m\right\}. \quad (7)$$

For the task of segmenting different ice types, the GLCP features are used as the image features. As indicated in Section 2.2, the individual GLCP feature generally can be modelled by a Gaussian distribution. The energy form E_F of the product of all $p(f_s^k|Y_s = m)$ can be written as:

$$E_F(f) = \sum_{s, Y_s = m} \left\{\sum_{k=1}^{K}\left[\frac{(f_s^k - \mu_m^k)^2}{2(\sigma_m^k)^2} + log(\sqrt{2\pi}\sigma_m^k)\right]\right\}. \quad (8)$$

4 Implementation Scheme

To implement the MRF model (Eq. (5)) requires estimation of four parameters: β (from Eq. (6)), α (from Eq. (5)), μ, σ. Estimation of $\mu = \{\mu_m^k\}$ and $\sigma = \{\sigma_m^k\}$ for each class requires training data. However, using an unsupervised environment, training data is not available. The expectation-maximization (EM) algorithm [20] is used to estimate μ and σ and is able to obtain a segmentation map. The EM algorithm for the MRF model (Eq. (5)) is outlined as follows.

1. A random segmentation result is initialized.
2. E-step: Estimate μ and σ from the feature data $F = f$ (which can be intensity feature or GLCP features) based on the segmented image:

$$\mu_m^k = \frac{1}{N} \sum_{s, Y_s = m} f_s^k,$$

$$\sigma_m^k = \left[\frac{1}{N-1} \sum_{s, Y_s = m} (f_s^k - \mu_m^k)^2 \right]^{\frac{1}{2}}.$$

3. M-step: Refine the segmentation result based on the estimated μ and σ by minimizing Eq. (5) using the Metropolis sampling with a simulated annealing scheme [21].
4. Repeat Steps 2 and 3 until a stopping criterion is satisfied.

The difficulty is that there is no closed-form solution for β and α in the EM algorithm. A commonly used strategy [21] is to priorily assign values to them by experience before executing the EM algorithm. Both parameters β and α function in the same manner by assigning weights to their corresponding energy components, and hence one of them can be fixed. Here, β is fixed to be 1 and only α is required to be adjusted. As the weighting parameter α is normally set as a constant parameter, the segmentation result often falls into three cases.

First, if the constant parameter makes the region labelling component dominant, the values of estimated parameters μ and σ may deviate considerably from the feature data and the segmented result is not consistent. Second, if the constant parameter makes the feature modelling component dominant, spatial relationship information would be ignored in the final segmented result. Third, if a balance can be achieved between both components by choosing a proper constant parameter, the estimated parameters are normally not globally but locally optimal.

The root cause is that the MRF-based segmentation model is very easily trapped in local maxima due to the spatial homogeneity constraint imposed by the region labelling component. As a result, the feature modelling component might not be able to learn the global parameters (i.e. μ and σ for each class).

A robust implementation scheme proposed in [10] is employed here to solve this problem by making the weighting parameter α vary during unsupervised segmentation. The introduction of the variable weighting parameter should not only enable the segmentation procedure to learn the global parameters of the feature modelling component but also impose spatial homogeneity constraint on the label distribution (through the region labelling component). For such purpose, the parameter may vary with respect to the annealing procedure. This work chooses the following function for the variable weighting parameter α:

$$\alpha(t) = c_1 * \gamma^t + c_2, \ 0 < \gamma < 1, \tag{9}$$

where γ, c_1 and c_2 are constants and t represents the t^{th} iteration. Experimentally, we have determined that setting $\gamma = 0.9$, $c_1 = 80$ and $c_2 = 1/K$ (where K is the dimension of the feature space) are appropriate values for a variety of imagery. Using this function, the feature modelling component will first (when $\alpha(t)$ is larger) dominate the MRF model in order to learn its global parameters and then (when $\alpha(t)$ is close to c_2) interacts with the region labelling component to refine the segmented result. Thus the energy of the simple MRF model can be rewritten as:

$$E = E_R + \alpha(t) E_F. \tag{10}$$

5 Experimental Results

5.1 Testing Methodology

Four methods are compared for image segmentation: (1) the MRF model with a variable weighting parameter (promoted in this paper), (2) the MRF model with a constant weighting parameter [8] [9], (3) the K-means clustering method [6], and (4) the finite Gamma mixture model followed by a maximum likelihood classification [5].

The first two segmentation methods are implemented by the EM algorithm: an iteration of E-step and M-step as discussed earlier (in Section 4). A fixed number of iterations is used as the stopping criterion in the following experiments. The tests conducted in this work indicate that segmented results do not change appreciably after 150 iterations and the result at the 150-th iteration can be considered as final. The K-means clustering method is also iterative. The clustering procedure stops when there is no change for the label of every pixel. The initial seeds for the clustering are chosen randomly. The stopping criterion of implementing the finite Gamma mixture model occurs when the coefficient of each class changes less than 1 percentage (1%).

Following the research in [18], the parameters for extracting GLCP features are set as follows. The three shift-invariant statistics (contrast, entropy, and correlation) are advocated here. The window size is 7×7. One displacement ($\delta = 1$) and four orientations (0^o, 45^o, 90^o, 135^o) are chosen. The quantization level is set to 64. Thus, each pixel is represented by a 12-d vector of GLCP features.

To segment ice and water images, the intensity feature is used as the only image feature for each segmentation method. To segment multiple ice images, there are two sets of features to be compared: the intensity feature and the GLCP features. The Gamma mixture model is based on the distribution of intensity in an image and hence applied only on the intensity feature. The other three methods will be applied using both feature sets. All four segmentation methods are provided the number of classes depending on the specific image.

5.2 Ice and Water Imagery

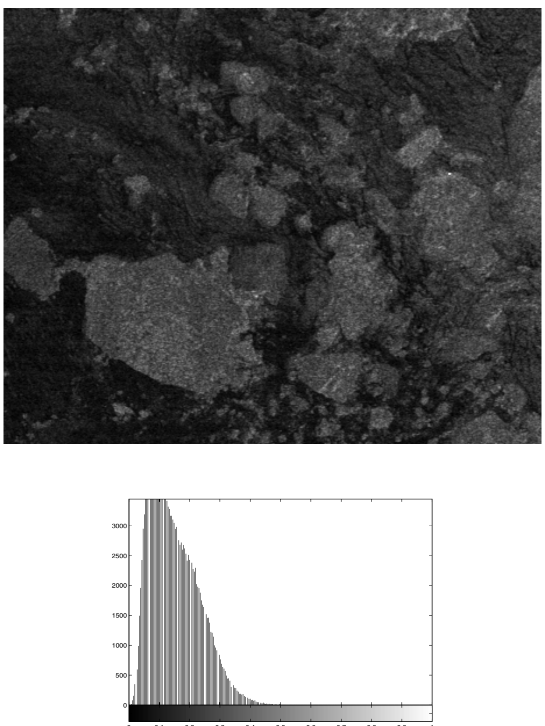

Figure 1: (a) Original C-band HH RADARSAT ScanSAR image (376 × 462 pixels, ©Canadian Space Agency) with ice (gray) and water (dark gray). (b) Histogram of the image (a).

The test image shown in Fig. 1(a) was extracted from the scene of a C-band HH RADARSAT ScanSAR data ($100m$ pixel spacing, 8 looks) covering Baffin Bay and Davis Strait acquired on June 24, 1998. It has a unimodal histogram (Fig. 1(b)). Fig. 2(c) shows the result obtained by the K-means clustering method. As the K-means clustering method does not take into account the spatial relationships, the segmented result is very sensitive to image noise and thus has many small or single-pixel regions. The same problem exists in the result obtained by the finite Gamma mixture model (Fig. 2(d)). Fig. 2(b) shows the result by the MRF model using a constant weighting parameter. It has improvement by removing most small regions over the K-means method and Gamma mixture model but still has some small regions. This is because the constant weighting parameter makes the region labelling component contribute less energy to the whole system than the feature modelling component so that the final segmented result does not incorporate sufficient spatial relationship information. The result segmented by the MRF model with the variable weighting parameter can however generate the most uniform regions (Fig. 2(a)) for water and ice and the preferred representation compared to the other three methods.

5.3 Multiple Ice Imagery

The test image shown in Fig. 3(a) is part of a C-band HH RADARSAT ScanSAR data ($100m$ pixel spacing, 8 looks) covering Baffin Bay and Davis Strait acquired on February 7, 1998. This image consists of three ice types: multi-year ice (bright areas), gray-white ice (light gray areas), and gray ice (dark gray areas). Its histogram of pixel intensity is unimodal. All four methods are applied over the image intensity feature and the GLCP texture features respectively. Only the segmented results using the GLCP texture features are shown in Fig. 3 for succinctness. The image intensity feature is not able to discriminate the three ice types. Also, as there is large intensity variance for pixels belonging to the same ice type, the spatial homogeneity constraint on neighboring pixels is very important for clustering the same-class pixels. As a result, the K-means clustering method (Fig. 3(d)) and Gamma mixture model are not able to cluster the three ice types due to their lack of spatial relationship information. The result by the MRF model with a constant weighting parameter (Fig. 3(c)) has some improvement over that by the K-means clustering method, but the means of three ice types are still confused and the segmentation is poor. The application of the MRF model with the variable parameter to the GLCP fea-

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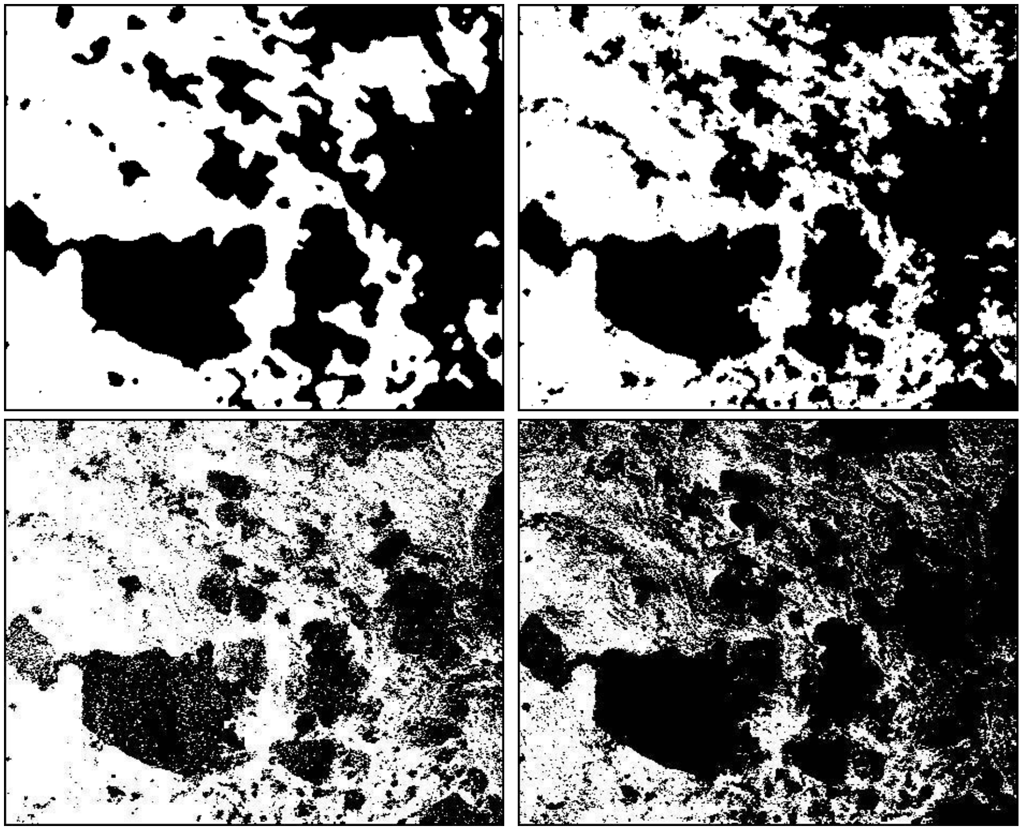

Figure 2: The arrangement of images is in the raster scanning order. (a) Segmented result by the MRF model with a variable parameter ($\alpha(t) = 80 * 0.9^t + 1$). (b) Segmented result by the MRF model with a constant parameter ($\alpha = 8$). (c) Segmented result by the K-means clustering method. (d) Segmented result by the finite Gamma mixture model.

tures is however able to generate the most accurate result (Fig. 3(b)).

6 Conclusions

The experiments demonstrate that the proposed segmentation method can be successfully applied to operational SAR sea ice imagery. In summary, the work in this paper makes the following contributions: First, the tonal feature is proposed to be used in partitioning ice regions from water regions and the GLCP texture features to segment sea ice types in multiple ice images; second, the finite Gamma mixture model and the K-means clustering method are extended to segment SAR sea ice imagery for comparison with the MRF-based segmentation model; third, the MRF-based segmentation model developed is able to utilize different kinds of image features and applied to segment SAR sea ice imagery; fourth, a variable weighting parameter is introduced to combine the region labelling component and the feature modelling component in the MRF-based segmentation model so that it can achieve a consistent unsupervised segmentation.

Future work will continue to improve the segmentation performance by taking into account other non-image factors such as season, radar look direction and incidence angle. A fully automatic segmentation algorithm is also expected to be developed which is able to use egg-coded information to generate an entire segmented scene.

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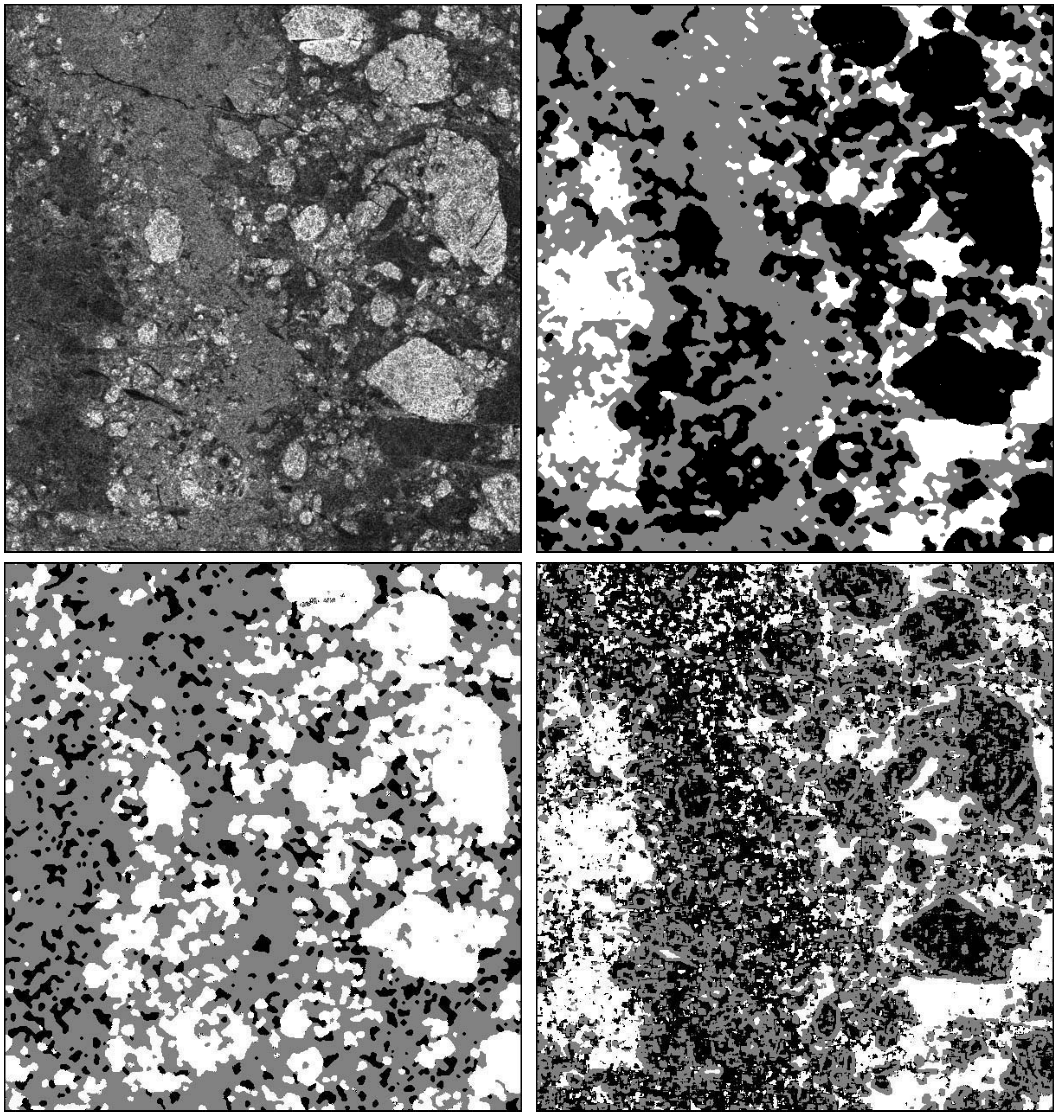

Figure 3: The arrangement of images is in the raster scanning order. (a) Original C-band HH RADARSAT ScanSAR image (631×595 pixels, ©Canadian Space Agency) with multi-year ice (bright areas), rough first-year ice (light gray areas), and smooth first-year ice (dark gray areas). (b) Segmented result by the MRF model with a variable parameter ($\alpha(t) = 80 * 0.9^t + 1/12$) using GLCP features. (c) Segmented result by the MRF model with a constant parameter ($\alpha = 6$) using GLCP features. (d) Segmented result by the K-means clustering method based on GLCP features.

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