Joint Image Segmentation and Interpretation Using Iterative Semantic Region Growing on SAR Sea Ice Imagery

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Abstract

Segmentation of images into disjoint regions and interpretation of the regions for semantic meanings are two central tasks in an image analysis system. Typically, the segmentation and interpretation are performed separately with the interpretation as a post processing of segmentation. In this paper, we use an iterative method that keeps refining the segmentation and producing semantic class labels at the same time. The segmentation algorithm is based on a region growing technique and the interpretation is a Markov Random Field (MRF) based classification. The two processes are integrated under the Bayesian framework, with both aiming at reducing a defined energy. The interactions between the two are bidirectional by letting the interpretation result have some degree of control on the region growing process. Various features can hence be efficiently combined, and accurate classifications are obtained for operational synthetic aperture radar (SAR) sea ice applications.

1 Introduction

Segmentation of images into disjoint regions and interpretation of the segmented regions are two central tasks in an image analysis system. As a fundamental step, image segmentation has received significant interest for many decades. There are numerous algorithms for segmentation of intensity images, examples including boundary based methods [5][14], region based methods [2][15], and hybrid techniques [3][13]. Most existing methods deal with a general definition of the segmentation problem and try to be applicable to a broad range of images. On the other hand, the interpretation step is application dependent, and various efforts [4][9][10] exist for different applications.

Typically, the segmentation and interpretation are performed separately, with the interpretation a postprocessing of the segmentation. A substantial deficiency of such a simple unidirectional link between the two processes is the fact that segmented regions may not match the real objects well enough for an accurate subsequent interpretation. In fact, segmentation is generally not a stand-alone problem but ill-posed if not associated with any implicit or explicit interpretation. Therefore, the interpretation needs to be able to guide the segmentation, and hence a bidirectional relationship between the two is desired.

We propose a joint segmentation and interpretation method under the Bayesian framework. The segmentation algorithm is based on a region growing technique [16] and the interpretation is a Markov Random Field (MRF) [8] based classification. Both aim at reducing a defined energy, and are combined in an iterative and interactive manner. During the iterations, the interpretation influences the segmentation by prohibiting merging between regions belonging to different classes (objects) based on current provisional interpretation result.

This concept of controlling region growing by interpretation result is known as semantic region growing [4][11]. A number of other works have also demonstrated success to various degrees in incorporating region (object) information into the segmentation process [6][7][12]. However, they are not iterative in the sense of the interaction between segmentation and interpretation. Their interpretation directly determines the region growing, which hence can be viewed as part of the interpretation process. From that perspective, their interpretation step is effectively postprocessing, and an inaccurate interpretation at the initial stage can be misleading for the overall process. Our work is substantially different in that the interpretation and segmentation are still two distinct processes and are iteratively refined in a cooperative manner. A hierarchical organization of the segmented regions can be formed during the iterations, which makes it possible to establish a reasonable match between the segmented regions and the objects. Such a match is crucial in incorporating object features such as shape.

Our application is the analysis of SAR sea ice imagery. Although research has been conducted [1][10] in this field for more than a decade, automated SAR sea ice analysis is

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still not operationally viable. SAR sea ice imagery is extremely complex and highly variable due to environmental factors, imaging parameters, and speckle noise. A successful system would need to integrate efficiently region features such as floe shape and existence of fractures, as well as the intensity and texture. Our method has provided such an integration.

The organization of the paper is as follows. Section 2 describes our proposed work. Section 3 presents experiment results on synthetic aperture radar (SAR) sea ice images. Future work comprises section 4.

2 Proposed Method

2.1 Segmentation

The region growing method for the segmentation in this paper is a modification of the hybrid region and edge approach presented in [16]. Its goal is to minimize the energy

$$\arg\min_{\Omega_1,\ldots,\Omega_n} \left\{ \sum_{i=1}^{n} \sum_{s\in\Omega_i} \left\{ \log(\sigma_i) + \frac{(y_s-\mu_i)^2}{2\sigma_i^2} \right\} + \beta \sum_{i=1}^{n} \sum_{s\in\partial\Omega_i} g(|\nabla(y_s)|) + \alpha \sum_{i,\forall l_i\in L_f} \sum_{s\in\partial\Omega_i} e_i(s) \right\} \tag{1}$$

where n is the number of segments, $\Omega_1,\ldots,\Omega_n$ are the obtained segments, y_s is the intensity of site s, μ_i is the mean intensity of segment Ω_i, σ_i is the standard deviation of intensity of segment Ω_i, and α and β are two positive constants. In the second summation term, $|\nabla(\cdot)|$ is the gradient magnitude, and $g(\cdot)$ is a monotonically decreasing function, which is formulated as

$$g(|\nabla(y_s)|) = e^{-(|\nabla(y_s)|/K)^2} \tag{2}$$

This function penalizes more for weak edges and less for strong edges, and the penalty difference between weak and strong edges is controlled by a parameter K. The last summation term in (1) is a shape related energy, which is specifically designed for the SAR sea ice application. Here, $e_i(s)$ is the error of site s in the ellipse fitting for the boundary $\partial\Omega_i$, l_i denotes the class (object) type for segment Ω_i, and L_f is the set of ice types that are characterized by floes for which ellipse shape segments, which correspond to individual ice floes, are favored.

The formulation in (1) assumes that the intensities of sites in each homogenous region are independent and Gaussian distributed. The first two summation terms are similar to the typical energy form in MRF based approaches [15], in which boundary pixels are penalized equally. In fact, this part of the formulation approximates the traditional MRF approaches if the parameter K in (2) is sufficiently large.

The merging order is a greedy one based on the first two summation terms in (1). Two segments are decided to be merged next if merging the pair of segments would decrease the summation of the two terms most among all, and also reduce the overall energy defined by (1) as well. When the overall energy cannot be further reduced, the penalizing parameter K is increased to start a new round of merging and interpretation. By doing that, we perform a similar segmentation as MRF based approaches but have included the edge strength and shape in guiding the process.

2.2 Interpretation

The interpretation is modelled by the MRF [8][9], which is an undirected network with nodes representing segmented regions and links representing symmetrical probabilistic dependence. Two nodes are linked neighbors if the two corresponding segments share a common boundary. For any node, MRF assumes its independence from others outside of the neighborhood given a neighborhood configuration. The joint probability of nodes is defined by Gibbs distribution [8]:

$$P(X=\mathbf{x}) = \frac{1}{Z} e^{-E(\mathbf{x})} = \frac{1}{Z} e^{-\sum_{c\in C} V_c(\mathbf{x})} \tag{3}$$

where C is the set of cliques which are defined as the sets of mutually neighboring nodes, $V_c(\mathbf{x})$ is the energy of configuration $\mathbf{x}$ on clique c, $E(\mathbf{x})$ is the total energy of configuration $\mathbf{x}$, and Z is a normalizing constant. Maximizing this probability gives the interpretation, and is equivalent to minimizing the summation of clique energies $\sum_{c\in C} V_c(\mathbf{x})$

For SAR sea ice interpretation, the domain knowledge include intensity, texture, shape, and existence of leads (long narrow fractures that ships can navigate through). Texture and shape are included in the computation of single node clique energy, while pair node clique energy incorporates the difference of mean intensity and the knowledge of co-occurrence of lead and certain ice types. The texture feature is measured by the Contrast (CON) of the grey level co-occurrence matrix [1], and thresholded to determine if it is coarse texture or not. The corresponding clique energy is defined as follows:

$$V_{tex}(\Omega_i|l_i) = \begin{cases} -\gamma_1 & \text{if both } \Omega_i \text{ and ice type } l_i \\ & \text{are with coarse texture} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Similarly, the ellipse fitting error is thresholded to determine if the segmented region is an ellipse shape. The corresponding clique energy is:

$$V_{ell}(\Omega_i|l_i) = \begin{cases} -\gamma_2 & \text{if } \Omega_i \text{ is of ellipse shape and} \\ & \text{ice } l_i \text{ has well defined floes} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Tone (intensity) difference is assumed to be Gaussian distributed, and the corresponding pair-node clique energy is the negative logarithm of this Gaussian pdf. Although co-occurrence of ice types can also be modelled in this log-prob manner, we use the following energy in order to simplify the training of the system

$$V_{co}(\Omega_i, \Omega_j | l_i, l_j) = \begin{cases} -\gamma_3 & \text{if ice type } l_i \text{ and } l_j \\ & \text{often occur together} \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

The above γ_1, γ_2 and γ_3 are all positive numbers so that the overall energy is decreased if the measurements are consistent with the knowledge. In the computation for (6), any water segment whose width over length ratio is less than a given threshold is deemed a lead.

2.3 The Overall System

The diagram of the overall system is shown in Figure 1. Watershed [14] is first applied for an initial segmentation, upon which the region adjacency graph (RAG) [8] is built. The iterative process begins with an interpretation step on the obtained segments using MRF and Gibbs sampler [8]. Merging of segments is then performed based on the interpretation result. When no further merging is possible, a new iteration begins with an increased edge penalty.

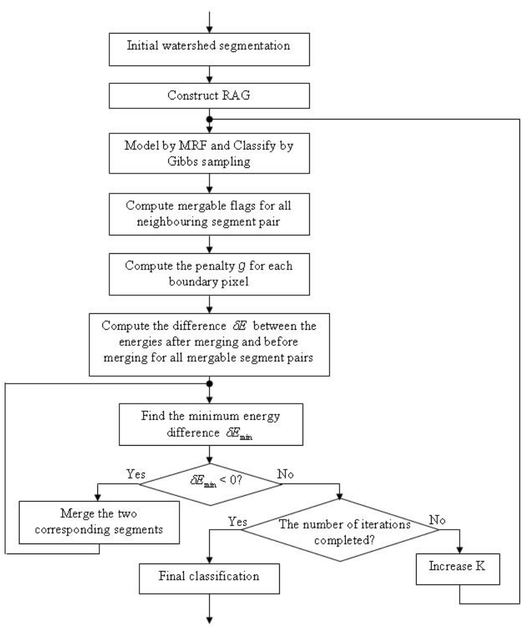

Figure 1. System diagram

3 Experiments and Conclusions

Figure 2(a)(c) show two SAR sea ice example images acquired by RADARSAT ScanSAR C-band mode with the resolution of $100m$. In (a), the center of the bottom is water and land. Regions relatively dark with brighter ridges inside are grey-white ice, and the rest are grey ice. Although the intra-class variations of grey-white ice is high, a good balance between details and smoothness of the segmentation has been achieved in (b) by the proposed method. In the second example of (c), the grey-white ice is relatively bright while the grey ice is relatively dark. Our method also produces an accurate result in (d), even though the intensity differences between ice floes are quite subtle. The bright lines are region boundaries before the final interpretation, and we note that the method is capability of preserving individual ice floes which is useful in identifying ice types. The proposed method has outperformed significantly existing methods such as histogram thresholding and MRF based segmentation on all tested images (18 in total). Due to limited space, such a comparative study is not presented in this paper. To conclude, the proposed method is operationally promising for the work that is currently completed by human operators at Canadian Ice Service.

4 Future work

The proposed method performs the solution searching in a bottom up manner on the hierarchical structure established during the process. More accurate results could also be obtained with a subsequent top down searching and adaptive updating of the structure.

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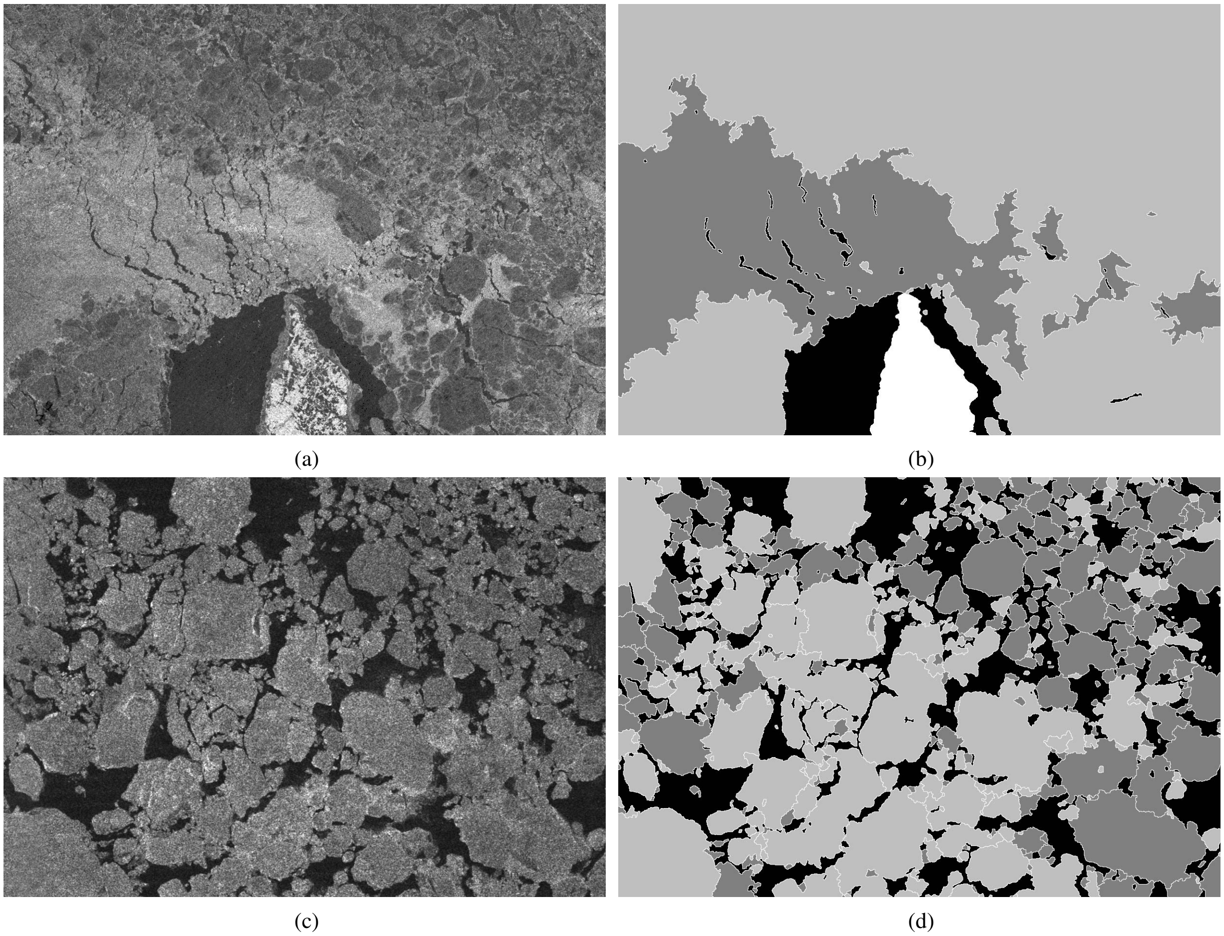

Figure 2. Segmentation of SAR sea ice images using proposed method

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