Operational Segmentation and Classification of SAR Sea Ice Imagery

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Abstract— **The Canadian Ice Service (CIS) is a government agency responsible for monitoring ice-infested regions in Canada's jurisdiction. Synthetic aperture radar (SAR) is the primary tool used for monitoring such vast, inaccessible regions. Ice maps of different regions are generated each day in support of navigation operations and environmental assessments. Currently, operators digitally segment the SAR data manually using primarily tone and texture visual characteristics. Regions containing multiple ice types are identified, however, it is not feasible to produce a pixel-based segmentation due to time constraints. In this research, advanced methods for performing texture feature extraction, incorporating tonal features, and performing the segmentation are presented. Examples of the segmentation of a SAR image that is difficult to segment manually and that requires the inclusion of both tone and texture features are presented.**

I. Introduction

Computer-assisted spatial information extraction from digital imagery is a necessity to support the processing of the volumes of remote sensing imagery now actively captured. This research focuses on applying computer vision techniques to the interpretation of synthetic aperture radar (SAR) sea ice imagery. The ultimate goal of this research is to develop computer-based algorithms to segment SAR sea ice imagery into salient categories. The primary data source is RADARSAT-1, a Canadian owned and operated SAR-based satellite. This research is performed in direct collaboration with the Canadian Ice Services (CIS), a government agency that uses about 4000 RADARSAT-1 scenes annually for monitoring all ice-infested regions in Canada's jurisdiction. This data is necessary to assist ship navigation through icy waters (eg. to support Canadian Coast Guard initiatives) and to calculate sea ice volumes for environmental monitoring (eg. to build scientists' understanding of global warming). Development of consistent and reliable computer-assisted algorithms to extract such information from remotely sensed imagery has been elusive; however, significant advances have been made in this field.

II. Background

A. Canadian Ice Services (CIS) Operations

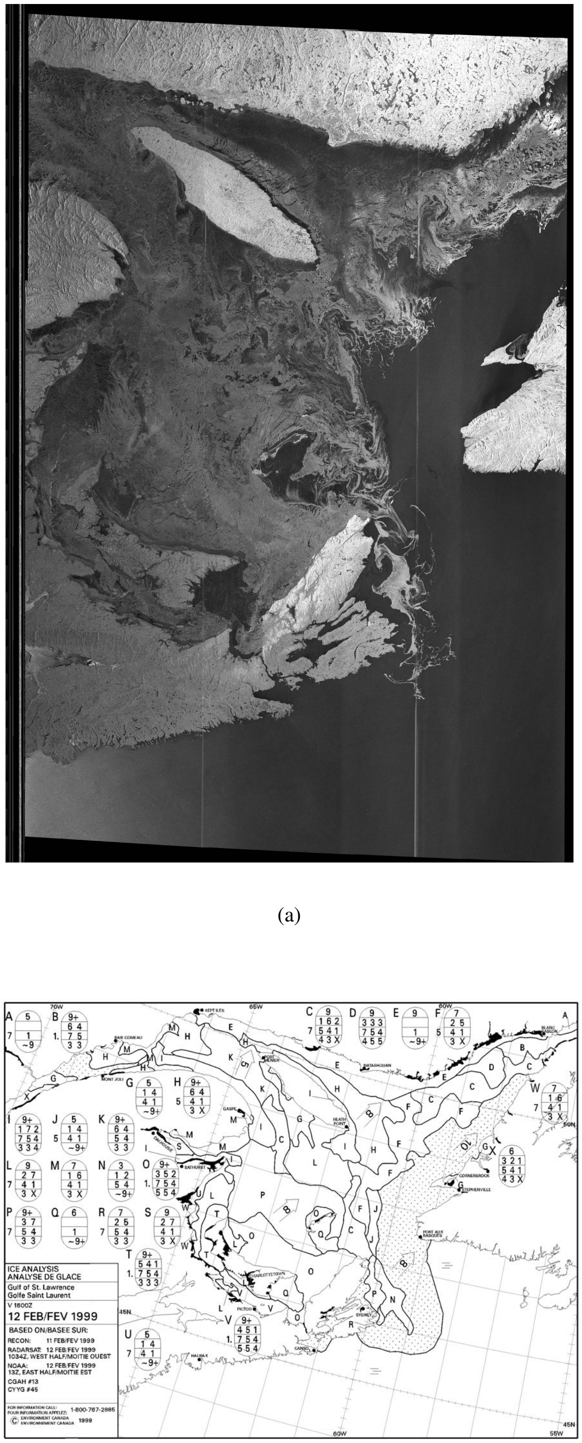
Fig. 1(a) depicts a RADARSAT-1 SAR sea ice image of the Gulf of St. Lawrence on February 12, 1999. These operational images obtained by CIS originally have 50 meter pixels, however, they are 2×2 block averaged to generate 100m pixels. This SAR image is used as the dominant source of information for generating the accompanying ice map (Fig. 1(b)). The entire ice map generation process is currently performed manually. The objective of this research is to design operational computer-assisted methods to generate a pixel-based segmentation of the region-based ice map. The ice analyst segments the SAR image into visually distinct regions. Then, the analyst assigns an "egg code" to each region to summarize the ice categories identified. These "egg code" regions typically contain two or more ice classes. The egg code stores the ice type, concentrations, and floe size and is a World Meteorological Organization (WMO) standard. Note that the SAR image is originally 5632 × 8120 pixels, and, as a result of scaling, the ice distinctions are not noticeable.

B. Need for Computer-Assisted Algorithms for Interpreting SAR Sea Ice Imagery

The need for automated analysis of SAR sea ice imagery has been clearly identified in the Canadian GCOS Plan for the Cryosphere. For example, the Sea Ice - Planning Element 3 (Effective Use of Remote Sensing Technology) is the continuation of the development of automated procedures at CIS to estimate geophysical parameters from RADARSAT [1]. Also, an NIC Science Plan indicates that one of the primary activities needed to be addressed is the development of SAR-based algorithms that can partially automate the generation of tactical ice products ([2], p. 10). A report prepared by Noetix Research Inc. for CIS outlines a number of specific tasks that can be supported with the use of automated procedures [3]. On an ongoing basis, CIS undergoes informal discussions with upper management with regards to computer-assisted algorithm development to create operational products (D. Flett, personal communication, May 2002).

C. Previous Computer-Assisted Efforts in Support of CIS Operations

The problem of automated sea ice identification in digital imagery is a difficult one. There exist other projects committed to developing automated methods for interpreting SAR sea ice imagery. These include a dynamic thresholding-based multi-year ice algorithm (University of Colorado), a knowledge-



(a)

(b)

Fig. 1. (a) RADARSAT-1 SAR sea ice image of the Gulf of St. Lawrence (capture February 12, 1999). (b) Accompanying ice map, produced primarily using this SAR image plus ancillary information sources.

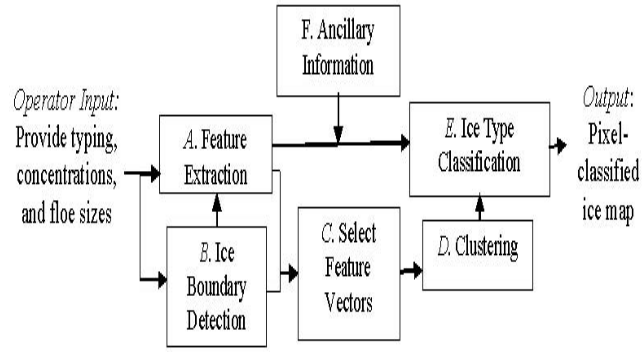


Fig. 2. Flowchart illustrating the proposed overall methodology for pixel-based segmentation of regions defined by egg codes. Research in this paper focuses on (A) texture and tonal feature extraction and (D) clustering.

based ice classification algorithm (ARKTOS, University of Kansas), and an ice/no-ice classifier (Noetix Research Inc.). Although technical advances, these algorithms have been deemed by CIS to be not appropriate to satisfy their operational needs. There are no known commercial software packages that have the necessary features required to interpret SAR sea ice imagery.

III. Developments in Computer-Assisted Segmentation of SAR Sea Ice Imagery

A. Strategy to Implement Computer-Assisted Methods

Fig. 2 depicts an overall methodology for generating pixel-based segmentations based on operator inputs to egg code regions. Texture feature extraction (A) is required since different ice categories produce visibly distinct textures in a radar-based image. Ice boundary detection (B) is important since the shape of the floe provides ice typing information. Features produced at ice class boundaries are misleading because they measure characteristics from multiple classes. By selecting those features (C) that are not on a floe boundary, a more robust feature set is generated as input into the clustering routine (D). Expert information is required to associate discovered classes with specific ice types (E). A means of integrating ancillary information (F) (ship reports, meteorological information, etc.) is required. The work in this research paper focuses on the use of texture and tonal features to directly, and in an unsupervised manner, segment regions when the number of ice categories is known.

The development of reliable, robust methods for the consistent classification of SAR sea ice types has been elusive, even though considerable effort has been made (see [4], [5]). There are two types of features commonly employed to characterize sea ice using SAR data. The first type is based on first order statistics such as tone, mean, variance and skewness. The second type is based on texture features. There is sufficient evidence to indicate that texture is more suitable than tonal features for describing SAR sea ice imagery [4], [5], however, the texture features alone may not be sufficient for discriminating the SAR sea ice data. Since the SAR image classes generally display differences in their intensities, the tonal features are still helpful for ice classification. Therefore, a fusion of tonal features and texture features is expected to achieve better performance.

The authors' significant research efforts for improving texture analysis of SAR sea ice imagery have been two-fold: improving the quality of derived texture features and comparing texture features for both classification and segmentation requirements. The next two subsections discuss these two topics.

B. Improved Texture Feature Extraction

There exist numerous texture feature extraction methods and these can be grouped into one of four categories: statistical, signal processing, model-based, and structural [6]. Structural methods have not been applied to the discrimination of SAR sea ice imagery due to the expectation of a repeating primitive, unlikely in the presence of speckle noise in natural landscapes captured by the SAR sensor. The other three categories have demonstrated potential for the role of characterizing textures in SAR imagery. The following focuses on three methods each commonly used in their own realms: Gabor filters (signal processing based), grey level co-occurrence probabilities (GLCPs) (statistically based), and Markov random fields (MRFs) (model-based).

1) Gabor Filtered Texture Features: Two-dimensional Gabor filters were original presented by Daugman [7] and the use of Gabor filters for image segmentation was advanced by Clausi and Jernigan [8], Bovik et. al. [9], and Jain and Farrokhnia [10]. Gabor filters are motivated by the fact that they are recognized to mimic aspects of the human visual system (HVS). Simple cells found in the visual cortex are recognized to be sensitive to limited orientation ranges and limited frequency bandwidths. Gabor filters can be formulated to also be sensitive to certain ranges of orientation and frequency.

Various scientists have tried to use Gabor filters for texture recognition with mixed results. Sometimes, the Gabor filters are not used properly, restricting their potential (see [11] for examples). A preferred Gabor filter bank that achieves classification accuracies that are stronger than those with the commonly used filter configuration is presented in [8]. In this paper, various frequency bandwidths, frequency spacings, orientation bandwidths, and orientation spacings have been compared. The preferred filter bank configuration required that the filters in the filter bank have 1 octave frequency spacing and bandwidth as well as 30 degree orientational spacing and bandwidth. The filter outputs were processed using the magnitude response, real component only, full wave rectification, sigmoidal function, and both geometric and central spatial-frequency moments. The magnitude response was identified as the preferred feature extraction method. A mathematical explanation for superiority of the magnitude response relative to using the real response is presented in [8]. Not surprisingly, spatially smoothing the filtered outputs (using the technique recommended by [9] dramatically improved the classification performance. The filter configuration derived and demonstrated in this paper is the filter configuration that is recommended for all texture segmentation work using Gabor filters.

2) GLCP Texture Features: Many scientists have attempted using grey level co-occurrence probabilities (GLCPs) [12] (otherwise known as the grey level co-occurrence matrix) for texture analysis of SAR sea ice imagery [13], [4], [14], [5], [15], [16], [17] as well as other remote sensing imagery [18], [19], [20]. A typical concern for practitioners is the proper selection of parameters to generate a meaningful texture feature set. In [4], the effect of grey level quantization on the ability of co-occurrence probability statistics to classify natural textures (eg. Brodatz and SAR) has been studied. As a function of increasing grey levels (excluding extremely coarse quantization), many of the statistics demonstrate a decrease in classification ability while a few maintain constant classification accuracy. Correlation analysis is used to motivate a preferred subset of statistics. The preferred statistics set (contrast, correlation, and entropy) is demonstrated to be an improvement over using single statistics or using the entire set of statistics. Testing is performed on Brodatz imagery as well as two separate SAR sea ice data sets.

3) Markov Random Field (MRF) Texture Features: A readable discussion of the theory and application of MRFs is presented by Li [21]. A typical MRF model is the Gaussian MRF (GMRF) model [22] which has been widely used for modelling image textures. The GMRF model is also a stationary noncausal 2-dimensional autoregressive process which is described by the following difference equation:

$$x_s = \sum_{s+r \in N_s} \beta_r x_{s+r} + \nu_s, \tag{1}$$

where r is the relative position with respect to the central pixel s, and $\{\nu_s\}$ is a stationary Gaussian noise sequence with zero mean.

β_r is the parameter describing directional information between pixels x_{s+r} and x_s. All β_r in the neighborhood system N_s forms the parameter vector $\beta = \{\beta_r | s + r \in N_s\}$. The property of the neighborhood system N_s is determined by its order and structure. The order of N_s determines the spatial range of the neighborhood.

This standard technique for generating MRF texture features creates anisotropic features. That is, features based on MRF models are usually sensitive to rotation of image textures. Given that SAR sea ice classes display both anisotropic and isotropic characteristics, a methodology has been developed that is able to produce circularly anisotropic MRF texture features that can be applied to rotationally invariant textures [23]. This is performed by, instead of sampling on a rectangular grid, capturing samples on a circular grid given an fixed orientation spacing. Given that the samples are highly correlated (due to dense representations on a finite discrete grid) this forces the least squares solution to produce a singular matrix. This singularity is handled using a novel approximate least squares estimate, demonstrated in the paper to produce sufficiently accurate estimates. A discrete Fourier transform (DFT) is applied to the generated MRF parameters to produce anisotropic texture features that can be applied to rotationally variant or invariant textures. These texture features have been demonstrated to be an improvement relative to other published work when applied to the classification rotated Brodatz image samples as well as SAR sea ice image classes.

C. Comparing Texture Methods

1) Comparing Texture Features for Classifying Pure Samples of SAR Sea Ice Imagery: Although many research papers investigate the use of specific feature extraction methods for remote sensing data, few papers compare these techniques. Texture features derived from MRF models have not been extensively studied for the purposes of characterizing the textures found in SAR sea ice image classes. A notable study [14] compares the MRF features to those produced by GLCPs and Gabor filters for characterizing SAR sea ice image texture. This work demonstrates that the texture features produced by Gabor filters and co-occurrence probabilities have a high correlation and produce classification accuracies that are not statistically different. MRF texture features, on the other hand, are uncorrelated with each of Gabor filters and MRF texture features. The two fused feature sets (Gabor filters plus MRFs and co-occurrence plus MRFs) demonstrate a statistically significant improvement compared to individual feature sets.

2) Comparing Texture Operators for Segmenting SAR Sea Ice Imagery: Even rarer than texture classification comparison papers are papers that compare different texture *segmentation* methodologies. Texture segmentation papers are rare possibly due to the higher level of expertise required, the difficulty associated with achieving operationally suitable segmentations of remote sensing imagery, and the difficulty of producing meaningful quantitative conclusions over limited test imagery. In [13], co-occurrence probabilities and MRFs are compared in the context of segmentation of SAR sea ice imagery. The role of window size in texture feature consistency and separability as well as the role in handling of multiple textures within a window are investigated. GLCPs are demonstrated to have improved discrimination ability relative to MRFs with decreasing window size, which is important when performing image segmentation. On the other hand, GLCPs are more sensitive to texture boundary confusion than MRFs given their respective segmentation procedures.

IV. Performing Segmentation

Four types of segmentation models are considered: finite gamma mixture model, K-means clustering, binary hierarchical K-means iterative Fisher (KIF), and Markov random field (MRF) modelling.

A. Finite Gamma Mixture Model [24]

This model is applicable to segmentation based on tone in a SAR image. Since each class' s grey levels can be described by a gamma distribution, a mixture model can be used to describe the entire image' s distribution. An iterative scheme is employed to estimate the individual class parameters. Assuming an image consists of a finite number (denoted by n) of classes and each pixel in the image is a mixture of these classes, the probability of each pixel can be represented by the following mixture model:

$$f(x_s) = \sum_{k=1}^{n} p_k g_k(x_s, \mu_k), \tag{2}$$

where x_s denotes the intensity of the pixel at site s, μ_k denotes the mean of the k-th class, p_k is the weight for the k-th class, and $g_k(.,.)$ denotes a probability distribution of the k-th class.

As the distribution of speckle noise in SAR image is normally gamma distributed, the function $g_k(.,.)$ in Eq. (2) can be assumed to be a gamma function:

$$g_k(x_s, \mu_k) = \frac{l^l}{\mu_k^l (l-1)!} x_s^{l-1} \exp\left(-\frac{l}{\mu_k} x_s\right), \tag{3}$$

where l denotes the number of looks.

If each pixel in the image is independently distributed according to Eq. (2), the joint distribution function for the entire image is

$$F(x) = \prod_{s=1}^{N} f(x_s), \tag{4}$$

where N is the size of the image and x is the vector of all pixels in the image. The log likelihood function for the image can be written as:

$$LF(x) = \sum_{s=1}^{N} \log f(x_s). \tag{5}$$

Given the constraint $\sum_{k=1}^{n} p_k = 1$, the parameters p_k and μ_k can be estimated by maximizing the log likelihood function $LF(x)$. As a close-form solution cannot be obtained from the maximum likelihood when $g_k(.,.)$ is assumed to be a gamma function in Eq. (3), an iterative method can be used for parameter estimation:

$$p_k^{t+1} = \frac{1}{N} \sum_{s=1}^{N} \frac{p_k^t g_k(x_s, \mu_k^t)}{f(x_s)} \tag{6}$$

and

$$\mu_k^{t+1} = \frac{1}{N p_k^t} \sum_{s=1}^{N} x_s \frac{p_k^t g_k(x_s, \mu_k^t)}{f(x_s)}. \tag{7}$$

The superscripts t and $t+1$ denote the number of iterations and $t \geq 1$. An initial estimate of p_k^1 and μ_k^1 is needed. The new value of p_k^2 is then substituted into Eq. (7) to solve μ_k^2. This process is repeated until p_k^t and μ_k^t converge. After the parameters p_k and μ_k are obtained, the maximum likelihood classification method can be used to classify all pixels. Experiments will demonstrate that this mixture model can well represent the data in SAR ice-water image.

B. K-means Clustering [25]

The popular K-means clustering method is employed here to cluster feature vectors to generate a segmented image knowing the number of classes a priori. This is appropriate, given that the operator-provided egg code information indicates the number of classes. The drawback is that K-means does not explicitly account for the spatial relationship between neighboring pixels. As the K-means clustering method is generally implemented according to the criterion of minimizing the Euclidian distance between feature vectors, it is necessary to normalize the fused features. The normalization should comply with a rule that each feature component should be treated equally for its contribution to the distance. The rationale usually given for this rule is that it prevents certain features from dominating distance calculations merely because they have large numerical values. As the feature vectors for segmentation are spread due to the presence of subclasses, it can be quite inappropriate to normalize the feature vector to be of zero mean and unit variance [25]. This paper uses a linear stretch method to normalize each feature component over the entire data set to be between zero and one. As the number of texture features used for fusion is overwhelmingly larger than the number of tonal features, it is reasonable to assign different weights to cases where the texture and tonal features are combined so that the contribution of tonal features is similar to that of texture features. A $50-to-50$ strategy is used to assign different weights to the texture features and tonal features after both are normalized.

C. Binary Hierarchical K-means Iterative Fisher (KIF) Algorithm [26]

The binary hierarchical K-means iterative Fisher (KIF) algorithm is a robust, unsupervised clustering technique that can be applied to the problem of image texture segmentation. The KIF component of the algorithm involves two steps. First, K-means is applied to a feature set. Second, the K-means class assignments are used to estimate parameters (mean and covariance) required for a Fisher linear discriminant (FLD). The FLD is then applied iteratively to improve the solution. This combined K-means and iterative FLD is referred to as the KIF algorithm. The binary hierarchical implementation of KIF operates by trying to separate a given set of feature vectors into two (by setting the number of classes in K-means to two). The process starts by considering the entire feature set. If this set can be broken into two distinct clusters, then an attempt is made to split those clusters into two clusters. This process follows a binary hierarchical tree until each of the clusters can not be split and, as such, the classes are identified. The Fisher criterion is used as a threshold to indicate whether or not a cluster should be split. The binary hierarchical KIF algorithm is used to properly segment images even though the number of classes, the class spatial boundaries, and the number of samples per class vary. The binary hierarchical KIF algorithm is fully unsupervised, requires no a priori knowledge of the number of classes, is a non-parametric solution, and is computationally efficient compared to other methods used for clustering in image texture segmentation solutions. This unsupervised methodology is demonstrated to be an improvement over other published texture segmentation results using a wide variety of test imagery and is well-suited to the case where there are many feature vectors per class.

D. Markov Random Field (MRF) Labelling

Not only can MRF methods be used to capture texture features, the same mathematical basis can be used to create segmentation models. A disadvantage of the gamma mixture model, K-means clustering method, and the binary hierarchical KIF for segmentation is that they do not account for the spatial relationships between neighboring pixels. Markov random field (MRF) models represent the probability distribution of image pixels depending on their neighbors and can be used as a labelling model to identify segmented regions. As a result, the MRF model-based method provides a means of incorporating spatial information into the segmentation process.

As the gamma mixture model (Section IV-A takes into consideration only the histogram of pixel gray levels, it is sensitive to speckle noise existing in the image and the final segmented image is not suitable for further applications such as ice boundary detection and ice concentration estimation. The refinement of such results can be achieved by taking local spatial relationship into consideration during segmentation. The MLL (multi-level logistic) model [21] has been proven to appropriately describe the spatial relationship. The integration of the gamma distribution of image intensity into the MLL model can form an MRF based labelling model which is then used to refine the results obtained by the gamma mixture model.

Most MRF based segmentation models use the multi-level logistical (MLL) model [21], [27] for modelling the label distribution. It is common for a segmentation task to choose the second order pairwise MLL model and define the potentials of all non-pairwise cliques to be zeros. The energy of the pairwise MLL model can then be written as:

$$E_R = \sum_s \beta \sum_{x' \in N_s} \delta(x_s, x'), \tag{8}$$

where $\delta(x_s, x') = -1$ if $x_s = x'$, $\delta(x_s, x') = 1$ if $x_s \neq x'$, and β is a constant which can be specified *a priori* [22].

The segmentation problem can be expressed in a Bayesian framework. Denote a random image by X and its segmented result by Y. The practical problem for segmenting a known image x is to maximize the probability of Y conditioned on $X = x$, denoted by $P(Y|X = x)$. According to the Bayes' rule,

$$P(Y|X = x) = \frac{p(X = x|Y)P(Y)}{p(X = x)}, \tag{9}$$

where $p(X = x|Y)$ denotes the probability distribution of the known image x conditioned on a segmented result Y, $P(Y)$ denotes the prior probability of Y, and $p(X = x)$ is the probability distribution of the known image x.

As x is known, $p(X = x)$ does not vary with respect to any solution $Y = y$ and hence can be disregarded since only the relative probability is of concern when maximizing $P(Y|X = x)$. $P(Y)$ can be assumed to be the probability of the MLL model with the energy function indicated in Eq. (8). Given that the number of classes and their means are known, $p(X = x|Y)$ can be assumed to be a Gamma distribution in Eq. (3). The energy of $P(Y|X = x)$ is then derived:

$$E = E_R + \sum_s \left[\frac{l}{\mu} x_s - (l-1)\log x_s - l \log l + l \log \mu + log(l-1)! \right] \quad (10)$$

The Metropolis sampling method [28] is used to implement this label model. To make the Metropolis sampling converge to the global minimum (energy), an annealing scheme should be used [29], [22]. The logarithmic annealing scheme proposed by Geman and Geman [22] is adopted here.

V. Examples of SAR Sea Ice Segmentation

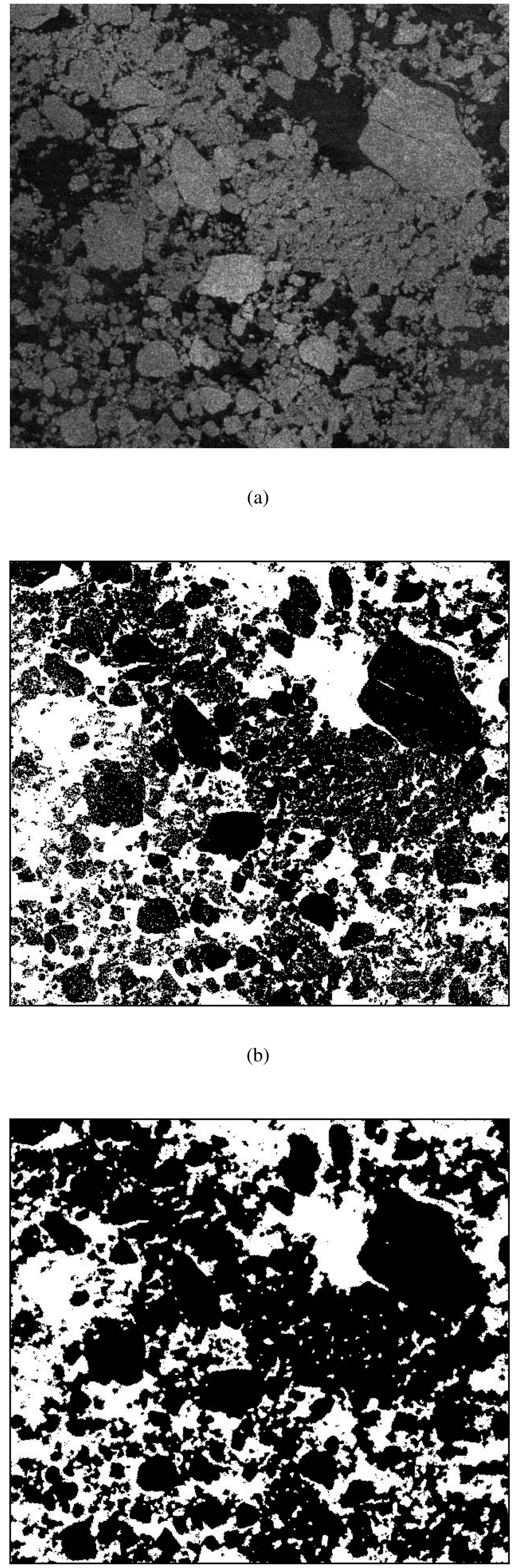
A. Ice-Water Segmentation

Ice analysts often need to estimate the ice concentration of a particular region in a SAR image, regardless of the specific ice types. The segmentation problem is to then segment the SAR image based only on ice and water classes. The associated histograms for these images are generally bimodal so a mixture model can be used to approximate such a histogram and obtain the individual components. As mentioned earlier, a Gamma distribution is used as a model in SAR image recognition. It is therefore reasonable to assume that an ice-water image is a mixture of two Gamma distributions.

Fig. 3(a) is part of RADARSAT-1 SAR image of Baffin Bay and the Davis Strait captured on June 24, 1998. This image consists of ice floes (bright regions) and open water (relatively darker regions). Fig. 3(b) shows the result following application of the gamma mixture model given the number of classes. As the gamma mixture model is sensitive to noise in an image for segmentation, the result shows non-uniform labelling of ice floes. A MRF model consisting of MLL model and a gamma distribution takes both the gamma distribution and local spatial relationship into consideration. As it may take a very long time for a Gibbs sampling method to converge, the result obtained by the gamma mixture model is used as an initial guess for the MRF based labelling model. Fig. 3(c) shows an improved segmentation result in comparison with Fig. 3(b). Using the results in Fig. 3(c), improved estimates of the true ice concentrations have been obtained.

B. Multiple Ice Classes

Consider the RADARSAT-1 SAR image of Baffin Bay and the Davis Strait captured on February 7, 1998 (Fig. 4(a)). Three different ice classes are apparent: multiyear floes (bright) are embedded in grey and grey-white ice. This image is difficult to segment using either computer vision or manual techniques. Fig. 4(b) represents the histogram of Fig. 4(a). Given that the histogram depicts a unimodal distribution, considering only tone will not achieve proper image segmentation.



(a) (b) (c)

Fig. 3. *Ice-water image consists of ice floes and open water.*

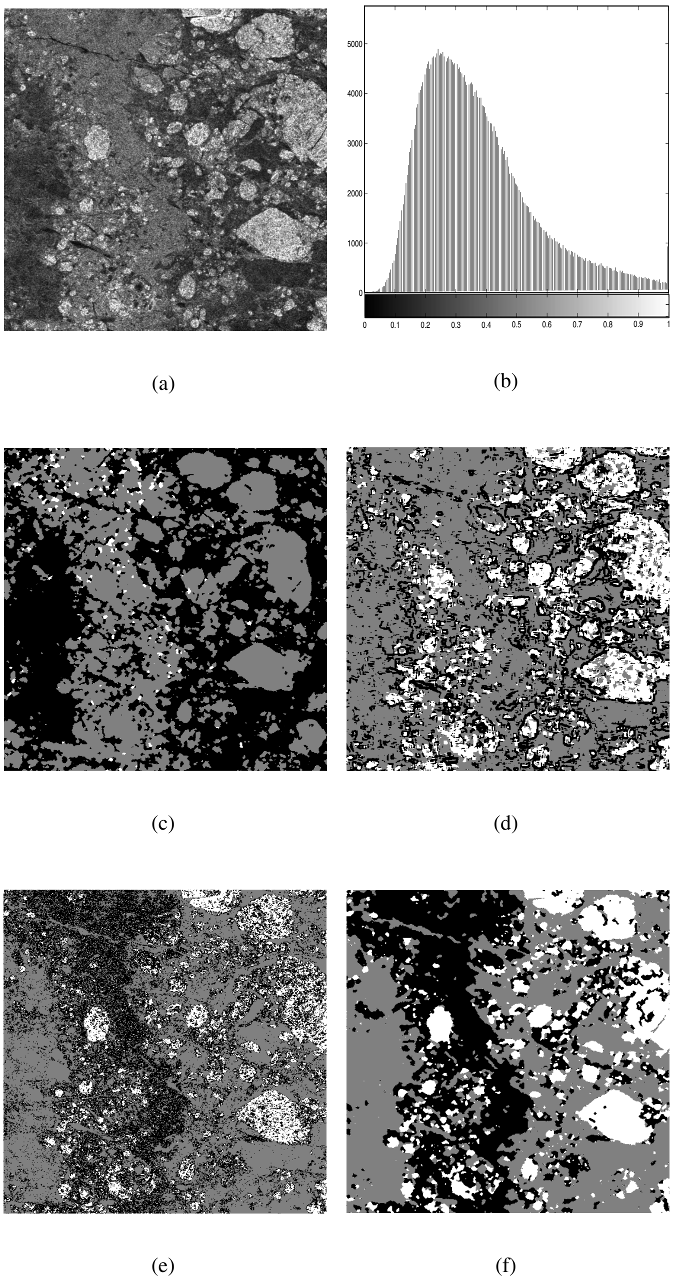


Fig. 4. (a) RADARSAT-1 SAR sea ice image of Baffin Bay and the Davis Strait captured on February 7, 1998. (b) Histogram of image in (a). Note the unimodal distribution. (c) Segmentation based on gamma mixture model. Poor segmentation since only tone used. (d) Segmentation based on GLCPs and K-means clustering. Poor segmentation since only texture used. (e) Segmentation based on fused texture and tone with K-means clustering. Improved segmentation. (f) Application of gamma MRF model applied to result in (e). Accurate segmentation performed in (f).

Fig. 4(c) represents a segmentation based on only absolute grey tones using a gamma mixture model. Only two of the three classes are identified due to multiyear and grey-white ice having similar tonal features and not being discriminated. Fig. 4(d) represents a segmentation based on using only GLCP texture features followed by K-means clustering. In this case, grey and grey-white ice are erroneously grouped together and multi-year ice is identified as a separate class. Fig. 4(e) represents a segmentation based on a fused feature set (GLCP texture + tone) followed by K-means clustering. Using the combination of tone and texture, all three classes are recognized, but not accurately. Fig. 4(f) represents an accurate segmentation resulting from applying a MRF label model to the result in Fig. 4(e). This figure displays a highly successful segmentation of the original SAR image. A combination of features (tone + texture) coupled with K-means (which acts an an initial guess) and MRF labelling (for refinement purposes) is used to produce this accurate segmentation found in Fig. 4(f).

VI. Future Direction

A number of future objectives are listed here.

1) The different components identified in Fig. 2 will be addressed through related efforts.
   - Ice boundary detection is an important part of the feature selection process, however, due to the nuances in the detection of edges in SAR sea ice imagery, this is a difficult task. We are actively developing dedicated means to uniquely identify sea ice boundaries.
   - Markov random fields as a basis for performing segmentation is an active research area. We continue to develop improved models for the inclusion of appropriate features to generate improved segmentations.
   - The MRF model provides a basis for inclusion of ancillary information. Future work will involve the incorporation of ancillary information in the underlying MRF segmentation model.
   - A means of associating the segmented regions with the known ice type names will require a means to implement expert, dedicated information into the classification framework.
2) To improve the existing feature set, a means of fusing Gabor and GLCP texture features has been initiated. This feature set shows tremendous promise to improve the texture analysis component of the overall process.
3) Segmentation using anisotropic, rotationally invariant MRF texture features is a topic that is unexplored in the research literature. The potential of this methodology will be explored.
4) A means of overlaying the ice map with the SAR sea ice image and removing and discrepancies will have to be implemented. The human operator is not perfect with respect to identifying the boundaries between egg codes

and these vague regions will have to be identified and handled properly.

VII. Conclusion

Reliable and consistent SAR sea ice image segmentation using computer vision is a very difficult problem. Manual generation of operational ice maps at the Canadian Ice Services is time consuming and the products potentially subject to human interpretation bias. Automated methods to segment the SAR sea ice images are expected to alleviate these problems. This paper illustrates methods to segment ice from open water and, subsequently, to classify the ice into its constituent categories. The gamma mixture model followed by a MRF label model is able to demarcate ice from open water regions. In the case of multiple ice types in the ice regions, both texture and tonal features are necessary to properly perform the segmentation. Here, the fusion of texture and tonal features leads to a more robust SAR sea ice image segmentation. Subsequent processing using an MRF label model dramatically improves the image segmentation so that operational information can be derived.

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