SEA ICE SEGMENTATION USING MARKOV RANDOM FIELDS

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Abstract- **Tools are required to assist the identification of pertinent classes in SAR sea ice imagery. Texture models offer a mean of performing this task. The texture information in SAR sea ice imagery can be characterized by two Markov random field models: the Gauss model for conditional distribution of the observed intensity image and the discrete model for the underlying texture label image. The segmentation can be implemented as an optimization process of maximizing a posteriori distribution in a Bayesian framework.**

1. INTRODUCTION

The interest in sea ice properties and behavior derives from their roles in areas such as navigation, offshore oil exploration, and climate modelling. With the development of remote sensing techniques, a vast amount of SAR sea ice imagery is being provided by satellite platforms. 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 the interpretation of these data.

The abundant texture information in SAR imagery is useful for segmentation of the pertinent ice types. Statistically based co-occurrence probabilities have been used to classify ice types in SAR imagery for years. This method suffers from having to select quantization, displacement, orientation values as well as the window size for building the gray level co-occurrence matrix. To explore a coherent theoretical framework to support more robust and more powerful algorithms is appealing. When model-based Markov random fields (*MRFs*) are used for texture analysis, they are demonstrated to have different abilities from the co-occurrence method [1]. Using *MRFs* methods, texture is analyzed as having preferred relations and interactions that can be articulated mathematically, and then a Bayesian framework can be employed to make inferences. Encouraging results have been obtained using *MRFs* for unsupervised Brodatz texture segmentation [2].

Sea ice is a complex and dynamic material. Its representation in a SAR image is dependent on many variables including SAR sensor properties, prevailing weather conditions, and geographical conditions. Many texture analysis papers use Brodatz imagery for testing [3] . Unfortunately, the texture appearance of a consistent ice type is not as regular as a Brodatz texture. Trained human operators often need ancillary information in order to properly segment a SAR sea ice imagery.In this case, the design of texture models and accurately estimating the model parameters will become a key concern for a successful segmentation.

2. IMAGE MODELS IN MARKOV RANDOM FIELDS

Observing an image, if it is not a random noise image, we can notice that the intensity value of a pixel is highly dependent on the intensity values of its neighborhood pixels. This phenomena can be called local similarity. In fact, in image processing, the notion of near neighbor dependence is pervasive. *MRFs* provide a mathematical tool to model this dependence.

The Hammersley-Clifford theorem [4] gives *MRFs* the ability to model global properties using local constraints. Because of this, *MRFs* models are commonly used priors in image processing. Let $X(i,j)$ be a random variable at a site (i,j) on the $N \times N$ lattice system S. For convenience, $X(i,j)$ can be labelled as X_s, $s = 1, 2, ..., M$ where $M = N^2$. The site r is a neighbor of s if $P(X_s|X_1, X_2, \cdots, X_{s-1}, X_{s+1}, \cdots, X_M)$ depends on X_r. Associated with each pixel is a set of random variables representing the states of the corresponding attributes of pixel s. For texture segmentation, we can define the image $X = \{X^I, X^L\}$ where X^I is the observed intensity image, and X^L is the texture label image corresponding to the intensity image where each label gives the texture type of the associated pixel.

Under this definition for the image X, our observation is not complete: we observe the intensity image, which can be called the degradation model, but not the label image. Our segmentation purpose is then to estimate the label image based on the degradation model and our prior information about the degradation model and the label image. Incorporating the prior information about the image X here means to select the appropriate *MRFs* models to describe the underlying structure of the intensity image and the label image. Viewing the literature, many models using *MRFs* are presented for various image processing problems. Krishmanachari and Chellappa [2] have demonstrated the applicability of using Gauss-Markov random fields (*GMRFs*) and pairwise interaction models to model the intensity image and label image respectively.

$\theta_{5,1}$	$\theta_{4,2}$	$\theta_{3,2}$	$\theta_{4,4}$	$\theta_{5,2}$
$\theta_{4,1}$	$\theta_{2,1}$	$\theta_{1,2}$	$\theta_{2,2}$	$\theta_{4,3}$
$\theta_{3,1}$	$\theta_{1,1}$	s	$\theta_{1,1}$	$\theta_{3,1}$
$\theta_{4,3}$	$\theta_{2,2}$	$\theta_{1,2}$	$\theta_{2,1}$	$\theta_{4,1}$
$\theta_{5,2}$	$\theta_{4,4}$	$\theta_{3,2}$	$\theta_{4,2}$	$\theta_{5,1}$

Fig. 1. Neighborhood structure of GMRF.

2.1. Pairwise Interaction Model

The local conditional probability of the label image can be modelled as [2]:

$$P(X_s^L = l_s | X_r^L, r \in \psi_s) = \frac{exp\{\beta U(l_s)\}}{\sum_{l'_s=(1,2,\cdots,L)} exp\{\beta U(l'_s)\}} \tag{1}$$

where ψ_s is the neighborhood set of a pixel s in the label image, and each pixel carries a class label $l_s, l_s \in \{1, 2, \cdots, L\}$. $U(l_s)$ is the number of neighbors in ψ_s that belong to same class as l_s.

2.2. Gauss Markov Random Field Model

Let η_s represent the neighborhood set of a pixel s in the intensity image. The structures of the *GMRF* model for different neighborhood orders are shown in Fig. 1. The vector θ contains the parameters shown in Fig. 1. If X^I is a *GMRF*, then the intensity value of a pixel can be written as [2]:

$$X_s^I = \sum_{r \in \eta_s} \theta_r X_{s+r}^I + e_s \tag{2}$$

where e_s is a zero mean, Gaussian noise. The conditional density of the intensity image X^I at site s which carries a class label l_s can be written as[2]:

$$P(X_s^I = x_s | X_s^L = l_s) = \frac{1}{\sqrt{2\pi\sigma^2(l_s)}} \exp\{-\frac{1}{2\sigma^2(l_s)}[x_s - \sum_{r \in \eta_s} \theta_r(l_s) x_{s+r}]^2\} \tag{3}$$

where σ^2 is also a parameter of the *GMRF* model.

3. SEGMENTATION IN A BAYESIAN FRAMEWORK

Based on the definition of image X, segmentation can be formulated as an optimization process involving maximizing a posteriori:

$$P(X^L | X^I) = \frac{P(X^I | X^L) P(X^L)}{P(X^I)} \tag{4}$$

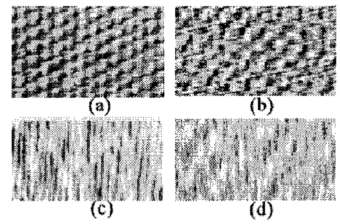

Fig. 2. Original and synthesized textures (a) Original cotton texture (b) Synthesized cotton texture (c) Original ripple texture (d) Synthesized ripple texture.

This approach is also called a *MAP* estimate: given the observed intensity image X^I, choose the most likely label image X^L which maximizing the posteriori distribution Eqn.4. Searching all the possible configurations of label image for a global optimum is computationally infeasible. To overcome the computational difficulty, the optimal solution can be obtained using a local optimization approach: the iterated conditional mode method *ICM* [5]:

$$P(X_s^L | X_s^I, X_r^L, r \in \varphi_s) = \frac{P(X_s^I | X_s^L) P(X_s^L | X_r^L, r \in \varphi_s)}{P(X_s^I)} \tag{5}$$

The distribution for $P(X_s^I | X_s^L)$ and $P(X_s^L | X_r^L, r \in \varphi_s)$ have been described in the previous section. Finally maximizing Eqn.5 is equivalent to assigning a label to each pixel to minimize [2]:

$$min_{X_s^L = l_s} \{ \frac{1}{2} \log(\sigma^2(l_s)) + \frac{1}{2\sigma^2(l_s)}[x_s - \sum_{r \in \eta_s} \theta_r(l_s) x_{s+r}]^2 - \beta U(X_s^L = l_s) \} \tag{6}$$

Minimizing Eqn.6 involves three tasks: model order decision, model parameters estimation, and pixel based segmentation. Model order is one of the most important concerns for a successful segmentation. Usually, the more complicated the texture, the higher order model should be used. Although using *MRF* models to describe the structure of the texture is theoretically appropriate, accurate estimation of the model parameters using the observed data is still an open issue. In our case, the parameters for the two image models mentioned in the previous section should be estimated. For pairwise interaction model, the only parameter β characterizes the binding between textures of the same class. In our experiment, β is set between 1 and 3. There are many existing methods for estimating the *GMRF* parameters, but none of them can guarantee both consistency and stability. The least squares estimate is selected, which can provide appropriate estimates for segmentation purpose and computational efficiency.The final step in the segmentation algorithm is pixel based deterministic relaxation which is an optimization processing by minimizing Eqn.6. This algorithm, called iterated conditional mode, was first proposed by Besag [5].

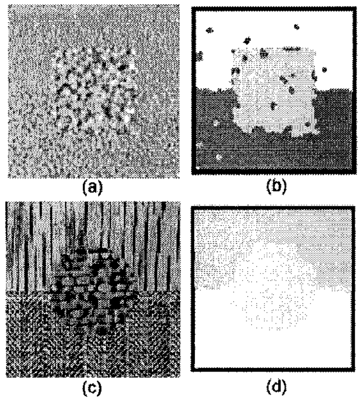

Fig. 3. (a) Synthesized textures and segmentation result (b) Brodatz textures and segmentation result.

4. RESULTS AND DISCUSSION

Some preliminary results are reported in this section. First the parameter estimation method is tested by synthesizing some *GMRFs* textures using the parameters estimated from texture images with known parameters as well as from observed images without knowing the parameters. The typical results of texture synthesis from the observed Brodatz images are shown in Fig.2. The cotton texture is synthesized using fifth order model while the second order model is more suitable for ripple texture. Fig.3 shows the segmentation results of synthesized and Brodatz textures. The Brodatz texture segmentation result is obtained using a third order model. In our experiment, the second order model cannot distinguish the middle texture from the others, and the fourth order model is very sensitive to the small local variation in the same texture. The sea ice data is extracted from X-band, HH polarization, STAR-1 SAR imagery of Mould Bay [6]. The ice types include first-year rough(FYR) and multi-year(MY) ices. The segmentation result is shown in Fig.4. Comparing the result with Brodatz texture, this algorithm dose not work currently well for ice imagery. We are working on obtaining a consistent estimation of model parameters for SAR sea ice imagery.

The underlying structure of texture determines the kind of *MRF* models that should be used for texture analysis purposes. The Gauss model has been successfully used in simulation, classification and segmentation of textures with structures can be modelled within a limited spatial range of pixel interaction. However, the larger order *GMRF* model cannot be used in practice because of the computational burden. In practice, it is also difficult to choose the most suitable model size for a given type of texture. Kashyap and Chellappa presented an algorithm [3] for quantitatively deciding the *GMRF* model structure. But one has to explore all the possible models to find an appropriate size, which is a process with combinatorial complexity.

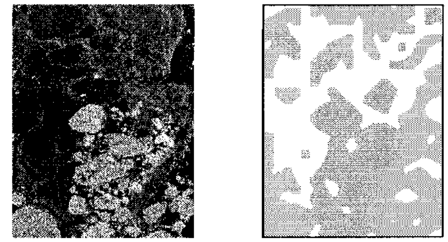

Fig. 4. (a) SAR sea ice image (b) Segmentation result.

5. CONCLUSIONS

Unsupervised segmentation of texture imagery is a difficult problem in computer vision. An algorithm for sea ice unsupervised segmentation using *MRFs* technique has been presented in this paper. This model-based *MRFs* method can be a candidate approach for sea ice segmentation. The main difficult of using this method is that the model structure and its parameters are unknown and need to be estimated from the given image before segmentation. For a robust application, more research needs to be performed in obtaining an appropriate model estimation method.

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