Improved Texture Recognition of SAR Sea Ice Imagery by Data Fusion of MRF Features with Traditional Methods

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***Abstract*- Image texture interpretation is an important aspect of the computer-assisted discrimination of SAR sea ice imagery. Co-occurrence probabilities are the most common approach to solve this problem. However, other texture feature extraction methods exist that have not been fully studied for their ability to interpret SAR sea ice imagery. Gabor filters and Markov random fields (MRF) are two such methods considered here. Classification and significance level testing shows that co-occurrence probabilities classify the data with the highest classification rate, with Gabor filters a close second. MRF results significantly lag Gabor and co-occurrence results. However, the MRF features are uncorrelated with respect to co-occurrence and Gabor features. The fused co-occurrence/MRF feature set achieves higher performance.**

I. Introduction

Synthetic aperture radar (SAR) is a powerful tool for resource management and environmental monitoring applications. Not only is SAR a sensor invariant to cloud cover and darkness, it is also especially useful for monitoring huge spatial regions that are not easily accessible. This is especially true for monitoring sea ice concentrations and extents. Sea ice information is important for assisting ship navigation in ice-infested waters and climate change monitoring in polar regions.

The development of robust methods for the consistent classification of SAR sea ice data has been evasive, even though considerable efforts have been attempted [1][2]. Since SAR sea ice imagery contains spatially dependent class characteristics, texture extraction methods have been commonly used to generate feature information for sea ice classes. The most common texture feature extraction method for remotely sensed data is the use of co-occurrence probabilities[3]. This paper compares the ability of three different texture feature methods to classify SAR sea ice image samples: co-occurrence probabilities, Gabor filters, and Markov random fields. The following research questions will be addressed:

Q1. Which method produces preferred classification ability?
Q2. Does combining feature sets generate an improved classification? Which combination of feature sets generates an improved performance?

II. Texture Methods

The three texture methods will be discussed in this section. Further details on the use of each of these methods for this study is found in [4].

A. *Grey Level Co-occurrence Probabilities*

Grey level co-occurrence texture features have been used for supervised classification of SAR sea ice imagery [1][2][3]. The co-occurrence probabilities are the conditional joint probabilities of all pairwise combinations of grey levels (i,j) in the spatial window of interest given two parameters: interpixel distance (δ) and orientation (θ). To generate texture features, statistics are applied to the probabilities. The selected statistics are dissimilarity (DIS), entropy (ENT), and correlation (COR). Orientations of θ = 0, 45, 90, 135 degrees and interpixel distance of 1 are used here.

B. *Gabor Filters*

A Gabor filter bank [5][6] is a pseudo-wavelet filter bank where each filter generates a near-independent estimate of the local frequency content. The technique for extracting texture features used here is based on a preferred technique developed by Clausi and Jernigan[7]. Filter bandwidths in the 2-d spatial-frequency plane are one octave and 30 degrees. To ensure average grey level insensitivity, the DC component of the filter is set to zero. Smoothing of the magnitude images as a function of the same Gaussian used in the Gabor function is performed[6].

C. *Markov Random Fields (MRFs)*

Markov random fields (MRFs) have been demonstrated to be quite effective for texture characterization[8][9][10]. A MRF is a random field with Markovian properties, namely, a point's value on the lattice is only influenced by particular neighbouring values. When p(X(c) | neighbours of c) is Gaussian, a difference equation can be used to represent the Markov process. The symmetric difference equation is:

$$X(c) = \Sigma\, \beta_{c,m}[X(c + m) + X(c - m)] + e_c$$

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where e_c is zero mean Gaussian distributed noise, m is an offset from the center cell c and $\beta_{c,m}$ is a parameter which weights a pair of symmetric neighbors to the center cell (these $\beta_{c,m}$ parameters represent the texture features). The summation is over all valid values for m as determined by the order of the model. In matrix notation, this equation is represented by:

$$X(c) = \boldsymbol{\beta}^T \mathbf{Q}_c + e_c$$

where $\boldsymbol{\beta}$ is a vector composed of $\beta_{c,m}$ and $\mathbf{Q}_c$ is a vector defined by:

$$\mathbf{Q}_c = \begin{bmatrix} X(c+m_1) + X(c-m_1) \\ X(c+m_2) + X(c-m_2) \\ X(c+m_3) + X(c-m_3) \\ \dots \end{bmatrix}$$

The parameters are estimated using a least squares approach. For every pixel in the window under consideration, a $\mathbf{Q}_c$ is determined. Then for every window, $\boldsymbol{\beta}$ is estimated which provides the texture features.

III. Testing and Results

A. Testing Methods

Detailed information concerning the RADARSAT-1 test imagery is contained in Yackel et al. [11]. Nine classes are considered for this texture study. This data set is difficult to classify for two reasons: (1) nine different classes are discriminated simultaneously and (2) relatively smaller window sizes (16x16) are used. Two sets of image samples were created. The "validated" data set contains those regions with field observations that were co-registered in the images. The "inspected" samples are based on regions that were in the same vicinity but not directly observed during the field program. Thirty-two non-overlapping samples of each class within each set were selected.

The Fisher linear discriminant (FLD) is used for classification. Kappa (κ) coefficients and associated confidence intervals (σ) are used to evaluate each error matrix. Statistical significance testing is performed to determine if one technique is performing statistically better than another. A confidence level of 5% is used (ie. 0.025 and 0.975 represent the confidence levels).

B. Hypothesis Testing and Results

Q1. Which method produces preferred classification ability?

Since there was no statistical difference between the results using validated data or inspected data for training, only combined results are presented. Three MRF orders (3, 4, and 5) were tested to determine which order produces more favourable results. Order 4 produced the best results and this order is used for the rest of the testing. Results comparing individual methods are displayed in the first three rows of Table 1. Co-occurrence results generated the best classification accuracies. Gabor filters performed favourably but not to the same extent as the co-occurrence method. MRF results were poorer than Gabor and co-occurrence results. Based on using independent feature sets, co-occurrence was demonstrated to be performing the best.

Q2. Does combining feature sets generate an improved classification?

Correlations of the different features provide insight into the potential for fusing the features and producing an improved classification. Correlation testing indicates that Gabor and co-occurrence features have relatively strong inter-feature correlations. What is most interesting is that MRF features are *not* well correlated with either of Gabor filtered or co-occurrence features. This indicates that the MRF features were providing unique information to the classification process. By combining MRF features with either or both of Gabor and co-occurrence, a more successful classification was expected.

Tables 1 (classification) and 2 (significance levels) reveal the outcome of fusing the feature sets based on using each method's preferred feature set. Gabor filters have a statistically lower classification success than co-occurrence features (0.013). However, fusing co-occurrence and Gabor feature sets combines redundant information since these two feature sets were strongly correlated. When Gabor filters were combined with the co-occurrence probabilities, there was no statistically significant change (0.315) and the classification accuracy actually dropped (from 0.494 to 0.478). Although the co-occurrence probabilities combined with the Gabor filters produced a significant improvement in the classification (0.962), the classification rate does not exceed that of using co-occurrence alone, which was the objective of fusing feature sets. As a result, using co-occurrence alone was a better alternative than combining co-occurrence with Gabor features.

TABLE 1
JOINT VALIDATION AND INSPECTED RESULTS

	κ	σ
(1) Co-occurrence	0.494	0.0231
(2) Gabor Filters	0.420	0.0232
(3) MRF order 4	0.167	0.0196
(4) Co-occurrence & Gabor Filters	0.478	0.0229
(5) Co-occurrence & MRF order 4	0.543	0.0226
(6) Gabor Filters & MRF order 4	0.495	0.0228
(7) Co-occurrence & Gabor Filters & MRF order 4	0.499	0.0227

TABLE 2
PAIRWISE SIGNIFICANCE TESTING BASED ON RESULTS IN TABLE 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	x	0.013	0.000	0.315	0.936	0.514	0.563
(2)	x	x	0.000	0.962	1.000	0.989	0.992
(3)	x	x	x	1.000	1.000	1.000	1.000
(4)	x	x	x	x	0.978	0.698	0.740
(5)	x	x	x	x	x	0.067	0.084
(6)	x	x	x	x	x	x	0.549
(7)	x	x	x	x	x	x	x

In contrast, the addition of MRF features to either of Gabor or co-occurrence produced improved results. The classification accuracy increased from 0.494 to 0.543 by adding MRF features to the co-occurrence features (statistical significance level of 0.936). Although this does not exceed the hard threshold of 0.975, it does indicate a strong improvement. Similarly, the classification accuracy increased from 0.420 to 0.495 by adding MRF features to the co-occurrence features (statistically significant improvement of 0.989). These results advocate the use of a combined co-occurrence and MRF feature set for classifying SAR sea ice imagery. Also, adding the MRF features to the fused co-occurrence/Gabor set improved the classification accuracy (from 0.478 to 0.499), however, the level was not statistically significant (0.740). This was in contrast to the fusing of a feature set with a correlated feature set. For example, fusing Gabor filters with a co-occurrence/MRF feature set decreased the classification accuracy from 0.543 to 0.499 (a strong significance level of 0.084). Fusing co-occurrence features with a fused Gabor/MRF feature set improved classification accuracy slightly from 0.495 to 0.499, but the significance level indicates that this change was definitely not significant (0.549).

IV. DISCUSSION AND CONCLUSIONS

The Gabor filter and co-occurrence probability methods measure texture features in SAR sea ice imagery basically by measuring local frequency. Gabor filters directly measure local frequency components by acting as a bandpass filter centred on the frequency of interest. The two co-occurrence measures that generally perform more strongly (dissimilarity and entropy) correlate well with local frequency measures. For example, smooth textures tend to have fewer entries in the co-occurrence matrix (low entropy) which are located close to the diagonal (low dissimilarity). MRF features measure something completely different about the local texture compared to Gabor filters and co-occurrence probabilities. Here, model parameters are generated to best fit a Gaussian distribution. However, there is no correlation between the MRF features and the co-occurrence or between the MRF and Gabor features. Yet, the MRF classification accuracy indicates that they provide meaningful information. Fusing MRF features with Gabor filter features improves the classification accuracy of using Gabor features alone. Fusing MRF features with co-occurrence features produces the same effect. The combination of MRF and co-occurrence features is advocated for improved texture feature recognition of SAR sea ice imagery since it consistently generated preferred results.

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