Sea ice classification using dual polarization SAR data

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Abstract. Sea ice is an indicator of climate change and also a threat to the navigation security of ships. Polarimetric SAR images are useful in the sea ice detection and classification. In this paper, backscattering coefficients and texture features derived from dual polarization SAR images are used for sea ice classification. Firstly, the HH image is recalculated based on the angular dependences of sea ice types. Then the effective gray level co-occurrence matrix (GLCM) texture features are selected for the support vector machine (SVM) classification. In the end, because sea ice concentration can provide a better separation of pancake ice from old ice, it is used to improve the SVM result. This method provides a good classification result, compared with the sea ice chart from CIS.

1. Introduction

Sea ice monitoring is very important in polar regions. One of the reasons is that sea ice is an indicator of the global climate change. Since sea ice has an important role in the heat exchange between the ocean and the atmosphere, it has an impact on the water temperature, heat circulation and ecosystem in polar regions. On the other hand, sea ice is a threat to the navigation and oil exploration, because it can make a damage to ships and oil platforms in the sea.

SAR proves to be an important tool for sea ice monitoring because it sends microwave rays which can penetrate rain and clouds, resulting in good monitoring capabilities during day and night. Especially, polarimetric information assists in sea ice monitoring.

Many studies show that polarimetric observation improves the sea ice classification and ice-water discrimination. For example, HH provides good contrast between new and gray ice types\cite{1} due to its strong sensitivity to surface scattering differences. However, when the intensity of the co-polarized return from open water is similar to the thin ice, HV is useful in distinguishing rougher thin ice from open water\cite{2}, because it is less sensitive to wind speed than HH or VV\cite{6}. Furthermore, Partington points out that in HV image the depolarizing character of the thin ice distinguishes it from the poorly depolarizing character of the open water\cite{2}. This agrees with Abreu’s study that in the HV image there is a superior contrast between wind-roughened open water and ice\cite{1}. The reason is that greater depolarization of backscatter over ice allows easy separation from water, which typically has a lower cross-polarization response since its backscatter is dominated by surface scattering\cite{1}. Furthermore,
HV has also been shown to have benefits in separating level from deformed ice [3] and first-year from multi-year ice[4].

2. Preprocessing of SAR Data
Two RADARSAT-2 ScanSAR images acquired over Beaufort Sea in HH and HV polarizations at 02:45:01 in October 5, 2009, are used in the classification. The size of each image is 10563 by 9999 pixels with the incidence angle range from 20° to 49°. In order to analyze the backscattering coefficients of different sea ice types, they are sampled in squares of 5×5 pixels in both HH and HV images. These types are open water (OW), new ice (NI), level gray ice (LGI), deformed gray ice (DGI), second-year ice (SYI) and multi-year ice (MYI). They are observed across the RADARSAT-2 swath with incidence angle step 1°, except that the OW occupies only from 20° to 38°, and the LGI occupies only 10°. The sampling has been completed by visual interpretation with the sea ice chart (Figure 1a) from the Canada Ice Service (CIS) as a reference.

Figure 1. (a) Sea ice chart from CIS  (b) The false-color image with HH (R), HV (G) and HV/HH (B)

2.1. Backscattering Coefficients as a Function of the Incidence Angle
Angular dependences of sea ice backscattering coefficients have been derived from the two images at HH and HV, respectively. The decrease in $\sigma^0$ as a function of the incidence angle for these various sea ice types is shown in Figure 2. It shows that in HH image the decrease of $\sigma^0$ is faster in absolute value for NI (-0.1979 dB/°) than for others, such as DGI (-0.1597 dB/°), SYI (-0.1525 dB/°), MYI (-0.1339 dB/°). And the value for OW is -0.7625 dB/°. However, the decrease in HV image is much slower and their absolute values are no more than 0.02 dB/°, except that the value for OW is -0.1084 dB/°.

Figure 2. $\sigma^0$ as a function of incidence angle for various ice types from (a) HH and (b) HV images

2.2. Backscattering Coefficients for Different Ice Types
In order to classify SAR images where $\sigma^0$ is a function of the incidence angle, the $\sigma^0$ values are normalized across the swath using 22° as a reference angle. A linear function is used for the
recalculation with -0.1553 dB/° as the calculated coefficient, which is the mean value of these sea ice types.

After the backscattering coefficients in HH image is recalculated, the probability density functions of various sea ice types are shown in Figure 3. In HH image, the value of OW is high with the mean value -8.14 dB, because it is wind-roughened. The mean value of NI (-19.43 dB) is low. In HV image, the value of MYI (-20.3 dB) is high, resulting from its depolarizing character. And the SYI (-23.42 dB) is lower than MYI. The OW (-27.13 dB) and the NI (-27.00 dB) values are close. In both HH and HV channels, the gray ice values are between the maximum and the minimum.

![Figure 3](image)

**Figure 3.** Probability density functions of $\sigma^0$, derived from (a) HH image normalized to 22° incidence angle and (b) HV image

### 3. Analysis of Texture Features

Gray level co-occurrence matrix (GLCM) has been used for texture feature extraction in many studies [9-11]. A number of texture features can be calculated from GLCM, such as mean, variance, homogeneity, contrast, dissimilarity, entropy, angular second moment and correlation. These features are calculated for different window sizes (11×11, 21×21, 49×49 and 79×79 pixels). The effective window size which can provide better separation of sea ice types is preferred. As is shown in Figure 4, windows of 49×49 and 79×79 perform better than the 11×11 and 21×21 ones. Given that the time cost of 79×79 is larger than that of 49×49, the 49×49 one is preferred.

![Figure 4](image)

**Figure 4.** Normalized mean values of texture characteristics for various sea ice types in different window sizes in (a) HH image and (b) HV image

When there is high correlation between two textural characteristics, they show similar properties of the ice types, and it makes no sense of using both features[5]. The correlation coefficients between all pairs of texture features are calculated and shown in the correlation matrices in Table 1. As is shown in Table 1, Group 1 (homogeneity and angular second moment) and Group 2 (variance, contrast, dissimilarity and entropy) in HH are negatively correlated. Mean and correlation are in low correlation.
with the two groups, respectively. Therefore, mean, correlation, homogeneity and variance in HH are preferred. And mean, variance and correlation in HV are selected in the same way.

Table 1. Correlation matrix for windows of 49×49 pixels in HH image. M=Mean, VAR=Variance, HOM=Homogeneity, CON=Contrast, DIS=Dissimilarity, ENT=Entropy, ASM=Angular Second Moment, COR=Correlation.

|     | M   | VAR  | HOM  | CON  | DIS  | ENT  | ASM  | COR  |
|-----|-----|------|------|------|------|------|------|------|
| M   | 1.0000 | -0.6695 | 0.6608 | -0.6216 | -0.6367 | -0.6808 | 0.6941 | -0.0122 |
| VAR | -0.6695 | 1.0000 | -0.9773 | 0.9923 | 0.9891 | 0.9787 | -0.9387 | -0.5289 |
| HOM | 0.6608 | -0.9773 | 1.0000 | -0.9842 | -0.9942 | -0.9974 | 0.9834 | 0.6350 |
| CON | -0.6216 | 0.9923 | -0.9842 | 1.0000 | 0.9975 | 0.9774 | -0.9378 | -0.5920 |
| DIS | -0.6367 | 0.9891 | -0.9942 | 0.9975 | 1.0000 | 0.9887 | -0.9592 | -0.6148 |
| ENT | -0.6808 | 0.9787 | -0.9974 | 0.9774 | 0.9887 | 1.0000 | -0.9888 | -0.692 |
| ASM | 0.6941 | -0.9387 | 0.9834 | -0.9378 | -0.9592 | -0.9888 | 1.0000 | 0.6357 |
| COR | -0.0122 | -0.5289 | 0.6350 | -0.5920 | -0.6148 | -0.6092 | 0.6357 | 1.0000 |

4. Classification Results

4.1. SVM Classification

The support vector machine (SVM) is implemented as the classification algorithm. And the selected texture features and the recalculated backscattering coefficients of HH, HV and HV/HH are used as inputs.

The classification result is as follows. Compared with the CIS chart, there is good water-ice discrimination. However, there is some confusion between the new ice and the old ice (including MYI and SYI).

![Figure 5](image1.png)  
(a) The SVM classification result and (b) the improved result with the concentration

4.2. Sea ice concentration

In this paper, sea ice concentration is used to improve the SVM classification result. Compared with the sea ice chart (Figure 1a), certain new ice near the open water is misclassified into old ice and this type of new ice, which is in small sizes, has high HV signal. This is consistent with the fact that the signal of multi-year ice in HV polarization can be higher than other ice types and open water, with the exception of consolidated pancakes[2].

Sea ice concentration is the proportion of the ice in the given area. And the new ice probably has low concentration due to the small ice floes surrounded by the open water, while the old ice probably has high concentration for the large ice floes are connected into the whole land. Therefore, the concentration of new ice and old ice, in some degree, can assist in the sea ice classification. After the
improvement by adding the ice concentration as one classification basis, the new result in Figure 5b is more consistent with the sea ice chart in Figure 1a.

5. Conclusion
An approach to sea ice classification using dual polarization SAR data is presented in this paper. In the first place, the normalized backscattering coefficients and effective texture features are obtained. The effective GLCM texture features are mean, correlation, homogeneity and variance in HH as well as mean, variance and correlation in HV. Then the SVM classification is implemented. The classification result shows good water-ice discrimination, which is important to the sea ice monitoring. However, certain new ice near the open water is misclassified into old ice. To solve this problem, sea ice concentration is used to improve the SVM classification result and the new result is more consistent with the sea ice chart.

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