Investigations into the X and C band Quad-Pol and simulated Compact-Pol features for sea ice classification

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Abstract

This paper explores the possibilities of quad polarimetric and simulated compact polarimetric SAR data for the purpose of sea ice classification. We propose an array of polarimetric features derived from the T_3 and S_3 scattering matrices, as well as from simulated compact polarimetric covariance matrices, both in C and X band. On a dataset of coincident TerraSAR-X (TS-X) and RADARSAT-2 (RS-2) acquisitions we perform a feature analysis in terms of relevance and redundancy for sea ice classification. The results are used to build an artificial neural network (ANN) based classifier.

1 Introduction

Sea ice monitoring has attracted increasing attention over the last few decades. Besides the scientific interest in sea ice, the operational aspect of ice charting is becoming more important due to growing navigational possibilities in an increasingly ice free Arctic. For this purpose, satellite borne SAR imagery has become an invaluable tool. Previously, mostly single polarimetric datasets were investigated in supervised and unsupervised classification schemes for sea ice investigation (e.g., [2, 4, 5, 3, 14, 19, 1, 9, 17, 16, 11]). Despite proven sea ice classification achievements on single polarimetric data, a fully automatic, general purpose classifier for single-pol data has not been established due to large variation of sea ice manifestations and weather and incidence angle impact. Recently, through the advent of polarimetric SAR sensors, polarimetric features have moved into the focus of ice classification research. The higher information content of two or more channels promises to offer greater insight into sea ice details and overcome some of the shortcomings of single-polarimetric classifiers. While dual-polarimetric data has already been investigated in a number of works, full-polarimetric data has so far not been investigated in only a small number of works (e.g., [18, 10, 13, 12]). After the launch of the RADARSAT Constellation Mission, yet another type of polarimetric imagery will be available for sea ice classification. For this reason, simulated compact polarimetric data generated from full-polarimetric data have been investigated as well ([7]). Building on these works , we intend to explore the potential of full-polarimetric and simulated compact polarimetric SAR data for the application of automated sea ice charting in Near Real Time (NRT) on C- and X-band. In our description we follow the steps of the processing chain: First, we propose an array of polarimetric features (Pauli based, lexicographic based, simulated compact polarimetry). The underlying dataset of our analysis consists of an array of two pairs of SAR acquisitions, near-simultaneously acquired and overlapping, one in C-band (RADARSAT-2, RS-2) and one in X-band (TerraSAR-X, TS-X) over ice infested areas. Each acquisition consists of two or three consecutive frames. Ancillary data from national ice services, SMOS data and expert judgment are utilized to identify the governing ice regimes and pick training datasets for the ice types. To gain quantitative insight into the quality of the features themselves, we employ mutual information to unearth the relevance and redundancy of features. The results of this information theoretic analysis guides a pruning process regarding the optimal subset of features. At this point we also discuss similarities and differences between different sensors in the feature quality analysis. In the second step of our processing chain (after the extraction of features), we perform a neural network based supervised classification on mentioned datasets and assess the classification accuracies for the different sensors by cross-validation.

2 Dataset

The list of datasets we use for our investigation can be found in Table 1. All acquisitions are quad-polarimetric, where the TS-X is StripMap mode with slant range resolution (Az./Rg.) 1.2m / 6m, and the RS-2 is FQ mode with slant range resolution (Az./Rg.) 5.2m / 7.6m . In order to arrive at an adequate assessment of dominant ice classes, we utilized ancillary data such as L3C SMOS based ice thickness charts, sea surface temperature charts and expert judgement of the SAR images and features. Since we are primarily concerned with establishing an automatic ice charting algorithm, we arrive at the following four dominant ice types (geared towards navigation purposes): open water/nilas (OW), young ice (YI), smooth first year ice (SFYI), and rought first year/multi-year ice (RFYMYI). The study area is located in the Arctic ocean, within 82.0°to 83.5°N and 9.0°to 22.5°E.

Figure 1: Overlay of all datasets. The left image cluster was acquired on 2015/04/19 with 94 min. lag, the right image cluster was acquired on 2015/04/23 with 59 min. lag. The slim, long acquisitions are TS-X image, the wider shorter ones are RS-2 images.

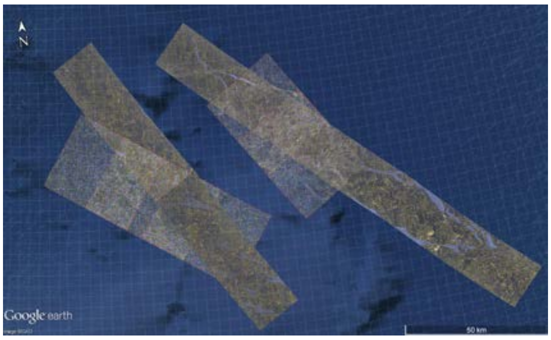

Table 1: TerraSAR-X and RADARSAT-2 imaging modes used in this study.

Date	Sensor	Inc. Ang. Rg.	Footpr. Az./ Rg.
2015/04/19, 14:51	TS-X	39° - 40°	115km / 17.5km
2015/04/19, 13:19	RS-2	21° - 23°	75km / 27km
2015/04/23, 13:43	TS-X	27° - 29°	150km / 17.5km
2015/04/23, 14:42	RS-2	36° - 38°	52.5km / 27km

3 Feature analysis

From the resulting scattering matrix S_3 we derive a number of features (e.g., Scattering Diversity, geometric intensity, surface scattering fraction, correlation, co-pol power ratio, real part of the co-pol cross product) which rely on the works of [15].
From the Pauli scattering matrix T_3, we derive the classical $H/A/\alpha$ features (see [6]). Since in future SAR missions, namely RADARSAT RCM, one will also be able to obtain compact polarimetric data over sea ice. In order to assess feature quality also for such data, we simulate compact polarimetric data from the full-polarimetric dataset. In particular we generate the $\pi/4$ Hermitian covariance matrix from $k_{\pi/4} = 1/\sqrt{2}(S_{HH} + S_{HV}, S_{VV} + S_{VH})$ and the Hermitian covariance matrix from $k_{CTLR} = 1/\sqrt{2}(S_{HH} - iS_{HV}, -iS_{VV} + S_{VH})$ in order to derive a number of CP features (see [8, Table 1], e.g. Stokes vector components, m-χ decomposition features, m-δ decomposition features).
When investigating the quality of the features with respect to ice classification, we employ the concept of mutual information to assess the relevance of each feature for ice type discrimination and possible redundancies between the different features. One key finding, for which we can also present an underlying analytical explanation, is the possible dispensability of Pauli based features for sea ice classification when using certain lexicographic basis features instead.

4 Classification results

After pruning the dataset based on the results in the previous step (feature quality analysis), we then fed the selected feature set into an artificial neural network classifier (ANN). For the final classification result we gathered for each acquisition data samples for each ice type and generated separate classifiers for different incidence angle ranges (near range 17°- 25°, mid-range 25°- 33°, far range 33°- 45°). In order to establish the stability of the classifier with respect to different choices of training datasets, we split the data sample sets into validation and training datasets. Interchanging roles of training set and validation dataset, we were able to find that the classification procedure is stable in terms of the choice of the training data. Despite noticeable biases of the sensors and incidence angle ranges towards certain ice types, the visual comparison of overlapping regions show similar ice structures in both the RS-2 and the TS-X image.

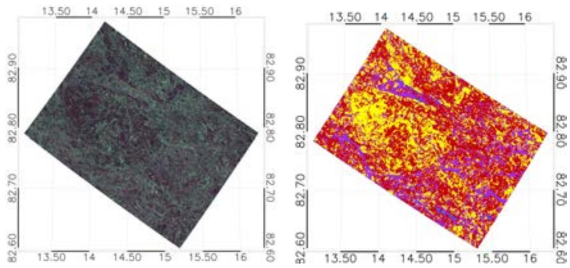

Figure 2: Left: Geocoded RGB composite of the RS-2 acquisition on 2015/04/19, 13:18 UTC. Right: ice classification. Blue: open water/nilas (OW), purple: young ice (YI), yellow: first year ice (SFYI), red: rough first year ice/multi-year ice (RFYMYI).

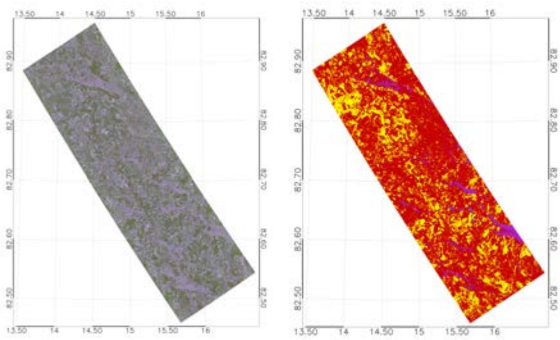

Figure 3: Left: Geocoded RGB composite of the TS-X acquisition on 2015/04/19, 14:51 UTC. Right: ice classification. Blue: open water/nilas (OW), purple: young ice (YI), yellow: first year ice (SFYI), red: rough first year ice/multi-year ice (RFYMYI).

5 Conclusion

We analyzed the suitability of full-polarimetric and simulated compact polarimetric features in X-band and C-band SAR imagery. To this end, we employed to pairs of spatially and temporally correlated acquisitions from TS-X and RS-2. We proposed a number of polarimetric features and analyzed their quality with respect to sea ice classification. We found in particular that, for the purpose of sea ice classification, Pauli features can possibly be discarded when including a certain array of S_3 based features. These findings were true both for the TS-X and the RS-2 data. We then performed on a pruned feature set the classification with an artificial neural network. The results show a reasonable visual match between the TS-X and the RS-2 images in the regions of overlap.

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