Towards Pan-Arctic Sea Ice Type Retrieval using Sentinel-1 TOPSAR modes

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Abstract

Sea ice monitoring has been subject to intense attention over the last few decades. Besides the scientific interest in sea ice, the operational aspect of ice charting is becoming more and more important due to increasingly ice free Arctic, resulting in growing navigational possibilities. Widely used daily pan-Arctic sea ice concentration maps are mainly derived from space-borne microwave radiometer data, with a typical spatial resolution of dozens of kilometers which are rather inadequate for navigational purposes. Since last few years, Sentinel-1a/b providing unprecedented spatial and temporal coverage of entire Arctic in C-band with its Extended Interferometic Wide Swath (EW) mode. Despite proven sea ice classification achievements on 'ScanSAR' type Synthetic Aperture Radar (SAR) images, a fully automated, operational classifier for has not been established due to large variation in sea ice manifestations and incidence angle induced impacts. Here we propose a methodology for Pan-Arctic sea ice type retrieval using Sentinel-1 (EW, HH-HV) dataset which accounts for the noises and incidence angle related impacts. Proposed supervised classification algorithm consists of two steps: The first step comprises of pre-processing, mosaicing and texture based feature extraction, the results of which are used to train a Support Vector Machine based classifier in the second step and used for subsequent sea ice type retrieval at pan-Arctic scale. Test results from the dataset acquired over the Northeast Greenland and Fram Strait showed that the classifier is capable of retrieving three broad ice types (Open Water, First Year Ice, Young Ice) with an overall accuracy of 99%.

1 Introduction

SAR systems have by now become an important tool for the scientific and operational monitoring of ice covered Arctic waters. Space-borne SAR surveillance is independent of daylight and cloud coverage. While optical sensors or airborne SAR cannot be used under adverse weather conditions or may simply be unavailable over remote Arctic regions, space-borne SAR can acquire images over a large regions on a regular and reliable basis. For about three decades, SAR satellites such as RADARSAT-1/2, ERS, or ENVISAT have been employed in scientific studies and regularly used by operational sea ice services. Until recently, majority of the operational ice services used C-band SAR images for regional ice charting using manual and time intensive visual interpretation techniques. The advent of Sentinel-1 constellation (1A and 1B), which is providing unprecedented temporal and spatial coverage over Arctic waters in dual polarization mode (HH-HV), warrants for an automated pan Arctic sea ice type retrieval methodology which can be employed on a daily basis to automatize the sea ice charting process, at least to some degree.

Most studies published so far on SAR based sea ice type classification, concentrate on single polarized data (e.g. [1, 8, 2, 7]). Such algorithms usually concentrates on classical image analysis tools. Among such tools are texture analysis via gray level co-occurrence matrices (GLCM), (cf. [5, 8, 1]), auto-correlation methods([3]) and Markov random fields (MRF)([6]). However useful and successful these techniques may be, there are still major obstacles in sea ice classification, that remain for all mentioned approaches. Most prominent issues are, the high backscatter variability of different ice types influenced by incidence angle, weather conditions and seasonal effects along with SAR system induced issues, e.g. thermal noise, swath order noise, azimuth scalloping etc. The proposed methodology is designed to minimize the two most prominent issues, SAR system induced noises and incidence angle related issues.

2 Dataset and Methodology

Overall in high Arctic the ice conditions usually comprised a mixture of Young Ice (YI), Smooth First Year Ice (SFYI) and Rough First/Multi Year Ice (RFMYI) along with small patches of Open Water (OW) between SFYI and RFMYI floes, refereed as leads. Due to certain limitation of dual polarimetric Extended Wide Swath mode images acquired by Sentinel-1a/b and lack of reliable in-situ measurements, we restrict ourselves to three major classes, i.e Young Ice (YI), Smooth First

Year Ice (SFYI) and Open Water (OW). We plan to introduce an the missing ice type, Rough First/Multi Year/ Deformed Ice (RFMYI), with the help of passive microwave products at later stage. As training dataset we chose small image patches from pre-processed and mosaiced SAR acquisitions representing each of the dominant ice types. Pre processing steps involved standard calibration, thermal and border noise removal followed by a multi-looking and land-masking process (using open street map) and finally mosaicing process. During the mosaicing process, we always sort the images by acquisition time and prepare the mosaic using latest available images on a specific day/time. Training data rectangles in the image were determined by visual judgment (e.g. using backscatter and GLCM feature images) in conjunction with archive data (Official ice charts produced by Norwegian Ice Services and local temperature) of ice situation for the location and time of the year. After selecting the training area we extracted a total of 8 GLCM based texture features along with their local variances to build a feature space. Details of each texture feature and their mathematical expressions are described in [7]. After extracting the features we train a Support Vector Machine(SVM) which are designed to classify a new mosaiced image derived from several Sentinel-1 individual EW images.

3 Classification Results

The processing chain was implemented in Python programming language which include image download and ingestion, pre-processing, mosaicing, feature extraction, statistical analysis and SVM training and classification). The processing time (in a cloud processing system) was 15 min in total for image preparation, feature extraction and classification for a area covering the whole of European Arctic at 50 meter spatial resolution . In order to validate the stability of the training process, we randomly split the initial training data patches into two disjoint subsets (training and reference samples). The classification results compared to reference data samples (as presented in Tables 1) exhibit a very promising accuracy, which underscores the stability of our algorithm. The percentages in the matrix indicate the proportion of samples of one reference class that were assigned to the respective ice type by the classifier. Therefore columns add up to 100%. Fig. 1 shows the classification results over a challenging sea ice covered area near north eastern part of Greenland along with pre-processed SAR backscatter images.

Table 1: Classification results compared to reference data samples from each class

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	Reference ice class		
ANN Result	OW	YI	SFYI
OW	100.0%	0.4%	0%
YI	0%	97.6%	0.6%
SFYI	0%	2.0%	99.4%

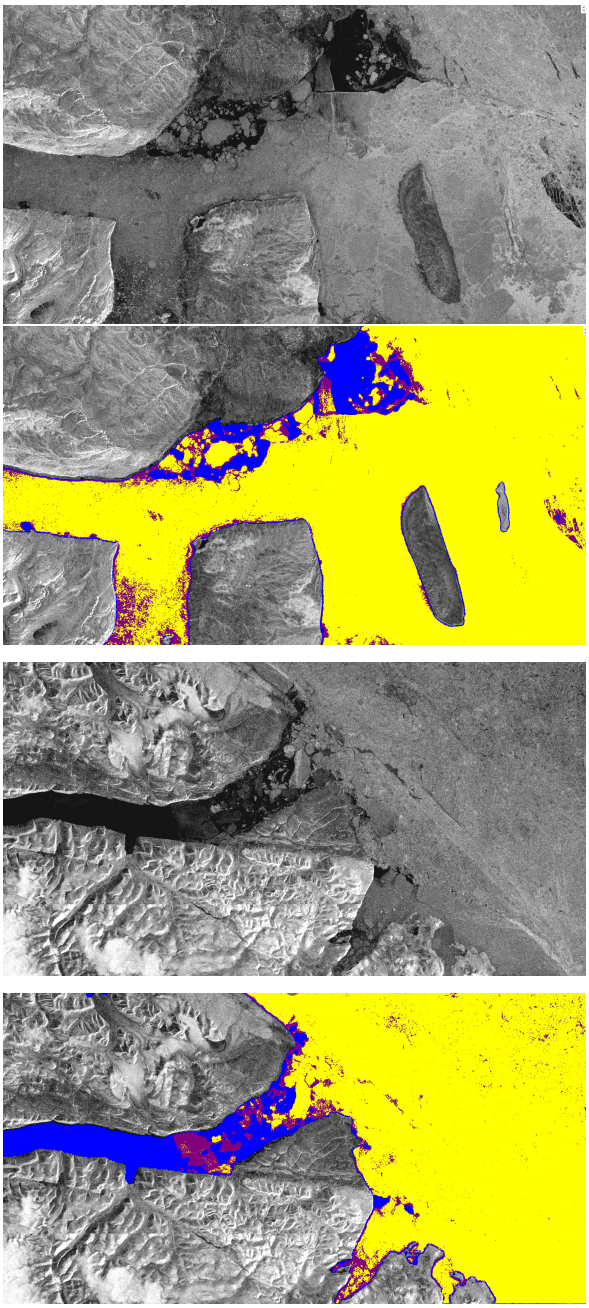

Figure 1: Top to Bottom: SAR backscatter mosaic obtained from several Sentinel-1 on 2018/11/20, between 00:00:00 UTC and 23:59:59 UTC. and Sentinel-1 based sea ice classification. **Legend:** Blue - Open Water/Nilas (OW), Purple - Young Ice (YI), Yellow - Smooth First Year Ice (SFYI).

Table 1 provides us with an overview of the SVM clas-

sifier performance on Sentinel-1 scenes acquired on . In terms of overall classification accuracy the proposed algorithm performed extremly well as the incedence angle and noise related issues were minimized before the classification process. When it comes to the differentiation between OW and other ice types, proposed algorithm performed extremely well. Young Ice (newly formed ice) is to some extend over represented in the marginal ice zone. We also remark that over the marginal ice zone the performance of the classifier becomes unreliable, specially during dynamic weather situation. This issue can be addressed with the help of ancillary datasets such as sea ice edge derived from passive microwave sensors.

It is observed that the selected sections of classified images (*i.e.* classified ice types) show good agreement with official ice charts from Norwegian Ice Services and National Ice Center. A thorough study on the comparisons will be presented in the final paper.

4 Conclusions

Until recently operational automatic sea ice classification using space-borne SAR was rather uncharted domain. We investigated the potential of ESA's Sentinel-1 data for automated sea ice classification in Pan-Arctic scale. We deem the distinction of all three classes are quite promising. Remarking that both training and validation data are from the same ice situation, our method displays consistency in itself and stability with respect to the choice of training data. Validation of the classification results with available in-situ measurement (from recent MOSAiC Expedition 4) and official ice charts are ongoing. Future work on improvement of the classification technique will include identification of optimum texture features and reduction of feature space which will facilitate shorter processing time. Furthermore we also plan to introduce an additional ice type, Rough First/Multi Year/ Deformed Ice (RFMYI), into our processing system with the help of operational passive microwave products.

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