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# Experiments with estimation of sea ice concentration using a convolutional neural network and microwave data

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***Abstract*—Using an existing convolutional neural network (CNN) framework that uses both synthetic aperture radar (SAR) data and passive microwave data to learn sea ice concentration (SIC), we test the inclusion of different passive microwave channels and also perturbing the labels used in the loss function. Improved results are found if the low frequency channels from the passive microwave data are included. We also find perturbing the labels may be a reasonable approach to improved SIC estimation in marginal ice zones.**

***Index Terms*—sea ice, synthetic aperture radar. convolutional neural network**

## I. Introduction

Sea ice concentration is considered an essential climate variable by the World Meteorological Organization (WMO) due to the key role it plays in climate. The two main sources of remote sensing data used for operational sea ice monitoring are passive microwave data and synthetic aperture radar (SAR) data. Passive microwave data have relative coarse spatial resolution (between 5 km and 55 km) and are typically used in the Arctic for automated sea ice concentration retrievals. Imagery from SAR sensors, in contrast, have relatively fine spatial resolution ($\approx$ 50 m) but due to the complexity of the radar signal and its interaction with the ice cover, it is difficult to interpret these images in an automated manner. At present, SAR images are typically analysed manually by trained ice analysts employed at national ice services. The products of these analyses, called ‘ice charts’ contain labelled regions, called polygons, that are considered to have spatially homogeneous ice cover. The labels contain the overall concentration of each polygon, in addition to other information on the ice cover. Although they contain errors due to operator biases, representativity errors, and uncertainty in setting ice concentration labels for intermediate ice concentrations [3] [1], they are still often considered one of the more accurate sources of information on sea ice concentration. Efforts to automate extraction of sea ice concentration from SAR have used these ice charts to provide labels in both feature engineering and feature learning approaches [5]. We focus on feature learning, specifically the use of CNNs.

Previous work using SAR data as input to a CNN has demonstrated that while this is a powerful approach toward automated use of this data, there are some typical problems that arise. For example, smooth ice, that appears dark in SAR imagery, can often be misinterpreted as open water. In a similar fashion, open water can often have spurious ice concentration retrievals due to wind roughening that is visible in the SAR image. To mitigate these issues one approach is to bring in another type of data into the CNN. Here we build on what has been done in a previous study [4] that uses passive microwave data with SAR to train a CNN. We also investigate an alternative interpretation of the ice concentration from the ice chart as labels for the CNN.

## II. Methodology

The input data to the CNN consist of patches of 300 $\times$ 300 pixels extracted from both HH and HV Sentinel-1 SAR imagery and 14 channels of data from the AMSR-E sensor. The SAR imagery are extra-wide (EW) swath mode images with a spatial resolution of 40 m $\times$ 40 m. The AMSR-E data consist of brightness temperatures at frequencies ranging from 6.9 GHz to 89 GHz at both horizontal and vertical polarization. We use the CNN structure from [4] that first reads in the SAR data, applies a spatial pyramid pooling module, followed by atrous convolution at four different dilatation rates, with a 1 $\times$ 1 convolution at the end to bring in the AMSR-E data. A full description of the input data and the CNN can be found in [4]. To train a CNN using ice concentration (here from ice charts) as labels, one option is to use the labels directly in the loss function with either a mean squared error, or mean absolute error, loss function. In this case, the model provides a prediction of ice concentration [2]. Alternatively one can threshold the ice concentration from the ice charts to zeros and ones and train a CNN to predict a probability of ice using a binary cross entropy (BCE) loss function. Recently, it has been shown that using ice concentration values directly in the BCE loss function, instead of first thresholding, yields improved model predictions [4]. In this brief paper we expand on this by interpreting the ice chart labels in a more direct probabilistic sense, and investigate the impact of this on the CNN model predictions. In our method, for each pixel in the sea ice chart, the label (a number between 0 and 1) is used as the probability $p$ in a single Bernoulli trial. Then the label at that pixel will be randomly replaced with either a one or zero with probability $p$ and this value of one or zero will be used in the BCE loss function. The method is only applied to labels that do not represent either open water or consolidated ice, to reflect the uncertainty associated with labels for intermediate ice concentrations. With regards to training the CNN, these random trials are repeated every single epoch. Before testing the label perturbation approach we will also show some results regarding the use of the AMSR-E data.

## III. Results

Our first set of results compare three different implementations of the AMSR-E data. For the first one the idea was to reduce smearing that could result from including the low frequency channels, which have coarse spatial resolution. Results from including only the last four channels of AMSR-E data (36.5 GHz H/V and 89 GHz H/V) can be seen in Fig 1 (middle row). It was found this lead to noisy predictions. This noise is significantly reduced when the 89 GHz channels are omitted (Fig 1, bottom row). Hence, the noise is likely from the CNN generalizing a pattern in the high frequency AMSR-E channels that could be present due to atmospheric moisture. We do note a possible slight blurring of the ice edge, with the low frequency channels included, although this could be mitigated by choosing a different probability threshold. Next, we investigated the method to perturb the ice chart labels. Our preliminary results (Fig 2) indicate this method is slightly better able to extract information in the marginal ice zone. Model predictions are less impacted over open water and consolidated ice, as expected.

## IV. Conclusions

Results shown here and further experiments carried out support the use of including the low frequency AMSR-E channels in tandem with SAR data in a CNN for estimation of sea ice concentration. Preliminary results perturbing ice chart labels shows it a reasonable approach. Overall, we find the ASIP database[1] a useful tool to investigate this problem for both academic problems in addition to being relevant for operational ice services.

1 https://data.dtu.dk/articles/dataset/AI4Arctic_ASIP_Sea_Ice_Dataset_-_version2

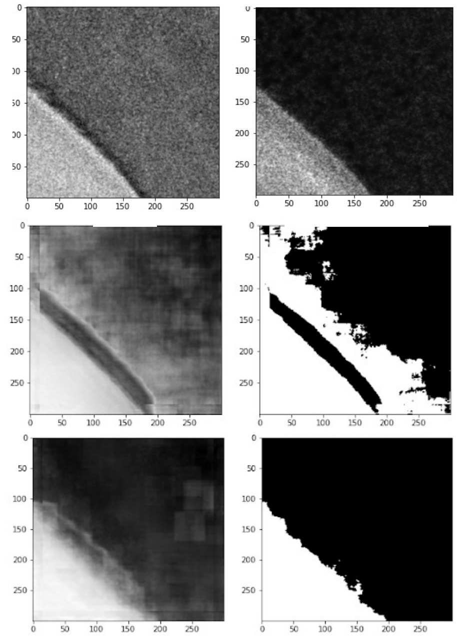

Fig. 1. CNN model predictions for a given patch, showing the impact of including the various AMSR-E channels. Top row; left, HH image patch; right, HV image patch. Rows 2 and 3, left, CNN predictions, right CNN predictions thresholded at 0.5. Middle row, predictions when only the 36.5 GHz and 89 GHz AMSR-E channels are used. Bottom row, model predictions including all AMSR-E channels except for 89 GHz (results are similar if 89 GHz is included).

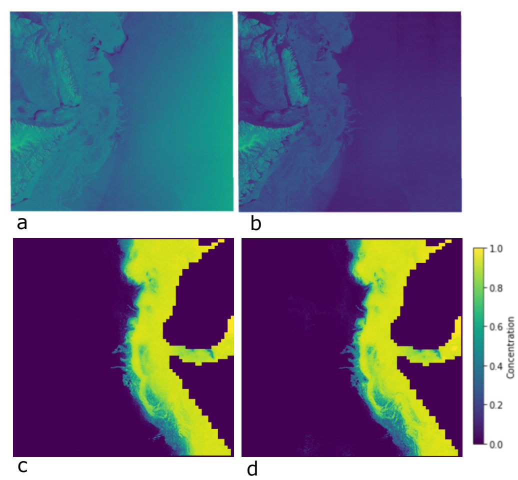


Fig. 2. CNN model predictions for a SAR scene acquired on March 22, 2018, covering Greenland's central east coast. Central latitude and longitude: 70.1° N, 19.7° W. a) HH image patch, b) HV image patch. Bottom row, CNN predictions when BCE is used without (c) and with (d) perturbed labels.

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