AUTOMATIC FEATURE LEARNING OF SAR IMAGES FOR SEA ICE CONCENTRATION ESTIMATION USING FEED-FORWARD NEURAL NETWORKS

Lei Wang, K. Scott, David Clausi

Department of Systems Design Engineering, University of Waterloo, Canada

1. ABSTRACT

A two-layer feed forward neural network is used to estimate ice concentration from SAR images directly in this research. SAR image patches are used as input. The CIS (Canadian Ice Service) ice concentration image analyses are used to train the neural network. The experiment shows that the simple neural network can be used to generate a reasonable ice concentration with no preprocessing to the SAR images.

Index Terms— SAR, sea ice concentration, neural network, regression

2. INTRODUCTION

Synthetic aperture radar(SAR) has shown its potential in sea ice monitoring in the Arctic region [1, 2]. Previous research has been focused on trying to use predefined features and mapping them to ice concentration through pre-defined mapping rules or fitted regression models [3, 4]. The effectiveness of this kind of method is determined by the selection of the features and the selected regression model which are both empirical. A more promising approach should be learning the features from data using less assumptions on the regression model or the features. The purpose of this work is to learn representative features directly from SAR images for ice concentration estimation. Neural networks have been used in ice water classification of SAR images [5, 6]. SAR image features such as autocorrelation are normally used as the input for the neural network. In a recent work by Karvonen [7], different features for each pixel of the SAR image is used as input in an two-layer neural network to estimate ice concentration. The neural network takes features of a single pixel as input, no relationship between nearby pixels such as texture feature is considered.

Similar to Karvonen's work [7], a two-layer feed forward neural network is used to estimate ice concentration directly from SAR images in this paper. Features are learned using only one hidden layer. The other layer is for regression between learned features and ice concentration. The difference is that the input of the neural network is the dual-pool SAR image patches instead of each pixel, so the spatial context information is incorporated. The ice concentration estimation is at the level of a group of pixels, as compared to other approaches for which this ice concentration is generally found over a homogeneous region. Initial results show the great potential of feature learning to estimate ice concentration.

3. DATA

The study area is located in the Beaufort Sea at the north of Alaska. This area is fully ice-covered in the winter and contains a mixture of ice and open water regions from July to September in the summer. One scene of Radarsat-2 dual polarized (HH and HV) ScanSAR narrow beam image is selected for the initial investigation (Fig. 1 (a)). It is acquired at Aug. 6th, 2010. It contains varied ice concentration and therefore appropriate for testing. The image analysis chart produced by Environment Canada is used as ground truth (Fig. 1 (c)). It provides eleven levels of ice concentration (from 0 to 1 with interval 0.1) information over homogeneous regions which are identified visually by a trained analyst.

4. METHOD AND EXPERIMENT

The neural network used in this experiment consists of two layers except the input layer. Each neural in the input layer output the SAR backscatter of a pixel. All the backscatters in a image patch is used as input. The hidden layer take the input layer and output the learned features. A sigmoid function is used as the activation function for this layer. Then a regression layer that uses linear activation function is used to generate the ice concentration. This layer fits the feature output from the hidden layer with the target variable in a linear regression model. Standard backpropagation is used as the training algorithm.

In our experiment, the patch size is set to 14 by 14. Different polarization combinations are tested. For single polarization, the number of neurons in the input layer is 196. For both polarizations, it is 392. SAR image patches and corresponding image analysis ice concentration are extracted using

This research was funded by Chinese Scholarship Council (CSC) and Environment Canada (EC). The ice concentration image analysis data were provided by Canadian Ice Service (CIS) of Environment Canada.

a sample pace of 10 km (The center of the image patches are equally spaced by 10 km) to train the neural network. There are 70% of the patches were used for training, while 15% were used for cross-validation and the rest 15% for testing.

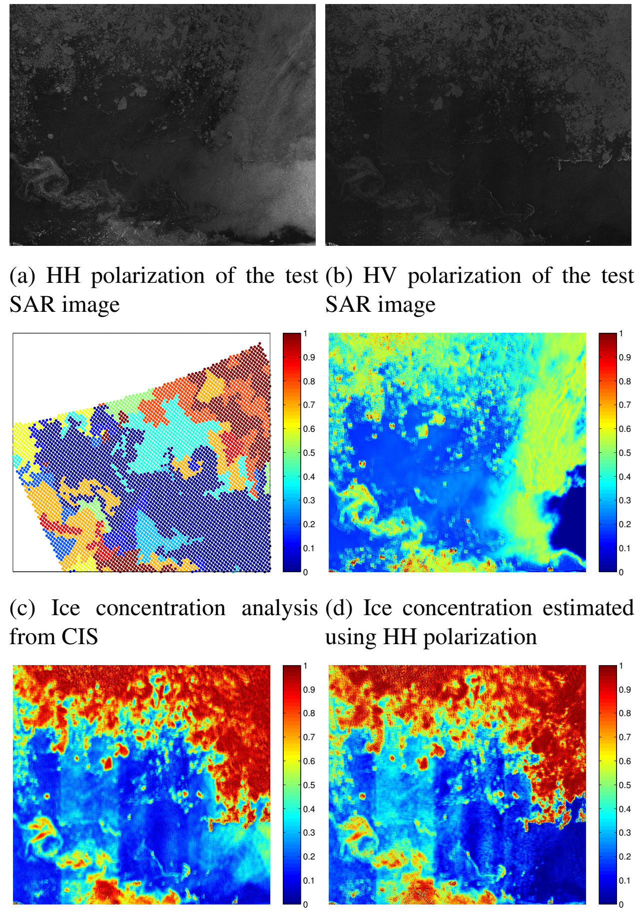
The results are shown in Figs. 1 and 2. In Fig. 2, the relationship between ice concentration from image analysis (ground truth) and ice concentration from the neural network for testing data is shown. . The line represents the mean value of the estimated ice concentration using neural network at certain ice concentration values, and the length of the vertical bars are the corresponding standard deviation of the estimated ice concentration. Correlation between the estimated ice concentration and the ground truth can be observed in all three different input band combinations. In Fig. 2, using only the HH polarization produces the worst result due to the incidence angle effect. Using both polarizations generate the best result. The estimation error in open water is smaller when using both HH and HV polarizations than only using the HV polarization. When using both HH and HV polarizations as the input, the incidence angle effect is not obvious in the result (Fig. 1(f)). So no incidence angle correction is needed. When the ice concentration is less than 30%, there is no monotone relationship between the estimated ice concentration and the ground truth. Ice concentration at this range is over estimated in general. This is mainly caused by the banding defect of the SAR image.

Use the trained neural network on the entire image generates the estimated ice concentration for the whole image (Fig. 1(d-f)). Ice concentration for each pixel can be roughly estimated using this method. No segmentation or local averaging is needed to smooth the resulted ice concentration.

This is only a two-layer neural network with 40 hidden layers. The ability of represent complex structures is limited. Multi-layer and larger neural networks are able to represent more complicated and higher level structures, and therefore, are expected to be more effective. With the most recent advances in deep learning in the past few years, it is now possible to learn mult-layer neural networks composed of millions of neurons. This will be the next step of this research.

5. CONCLUSION

The potential of feature learning in ice concentration estimation from SAR images is demonstrated by using a two-layer feed forward neural network. The results indicate that it is possible to extract the best features that represent ice concentration using this approach. On the other hand, problem caused by the effect of banding effect in HV polarization is still to be solved.



(a) HH polarization of the test SAR image (b) HV polarization of the test SAR image

(c) Ice concentration analysis from CIS (d) Ice concentration estimated using HH polarization

(e) Ice concentration estimated using HV polarization (f) Ice concentration estimated using HH and HV polarizations

Fig. 1: Test data and results.

6. REFERENCES

[1] K. Steffen and J. Heinrichs, "Feasibility of sea ice typing with synthetic aperture radar (SAR): Merging of Landsat thematic mapper and ERS-1 SAR satellite imagery," *Journal of Geophysical Research: Oceans (1978–2012)*, vol. 99, no. C11, pp. 22413–22424, 1994.

[2] T. Geldsetzer and J. J. Yackel, "Sea ice type and open water discrimination using dual co-polarized C-band SAR," *Canadian Journal of Remote Sensing*, vol. 35, no. 1, pp. 73–84, 2009.

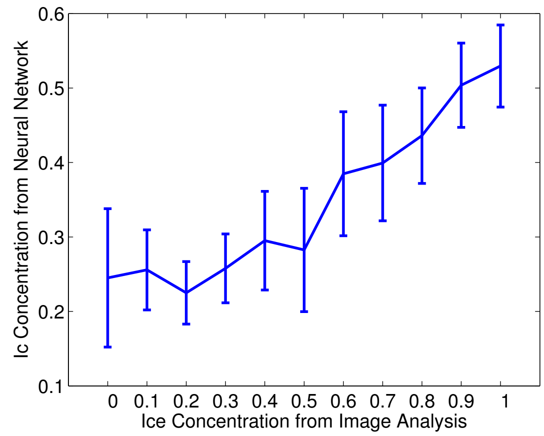
[3] J. Karvonen, B. Cheng, T. Vihma, M. Arkett, and T. Carrieres, "A method for sea ice thickness and concentration analysis based on SAR data and a thermodynamic model," *The Cryosphere*, vol. 6, pp. 1507–1526, 2012.

[4] J. Karvonen, "Baltic sea ice concentration estimation based on C-band HH-polarized SAR data," 2012.

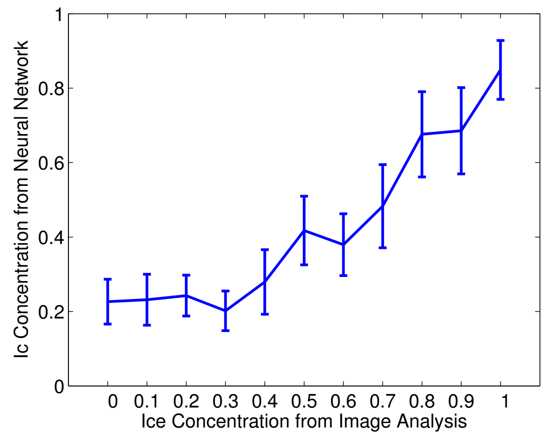
[5] N. Y. Zakhvatkina, V. Y. Alexandrov, O. M. Johannessen, S. Sandven, and I. Y. Frolov, "Classification of sea ice types in ENVISAT synthetic aperture radar images," *Geoscience and Remote Sensing, IEEE Transactions on*, vol. 51, no. 5, pp. 2587–2600, May 2013.

[6] A. Berg and L. E. B. Eriksson, “SAR algorithm for sea ice concentration-evaluation for the baltic sea,” *Geoscience and Remote Sensing Letters, IEEE*, vol. 9, no. 5, pp. 938–942, 2012.

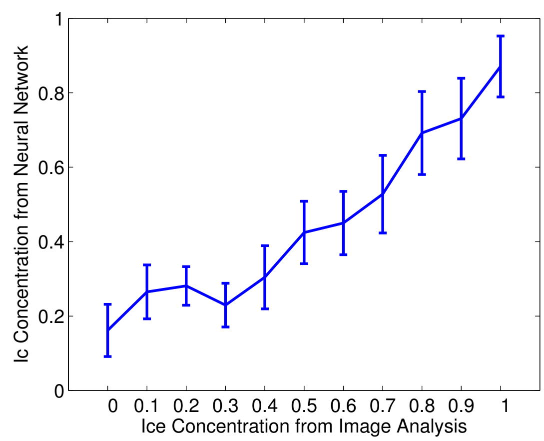
[7] J. Karvonen, “Baltic sea ice concentration estimation based on C-band dual-polarized SAR data,” *Geoscience and Remote Sensing, IEEE Transactions on*, vol. 52, no. 9, pp. 5558–5566, 2014.



(a) Error bar of neural network regression using HH.



(b) Error bar of neural network regression Using HV.



(c) Error bar of neural network regression using HH and HV.

Fig. 2: Error bars of the testing results. The line and length of the vertical lines are the mean values and standard deviations of neural network output at corresponding ice concentrations.