ID25: Automating validation of satellite-derived ice-cover features: Discriminating ice objects in optical ice images with different degrees of local texture distortions

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Background and motivation: The amount of data from satellite missions is expected to increase. In fact, this number increases faster than the capacity of experts to process, adequately validate and evaluate the uncertainty of the results. Despite rapid progress in machine learning, the methods and standards for automated interpretation of sea ice imagery remain underdeveloped. One such field is the automated interpretation of ice imagery from ground operations, especially under poor visibility conditions (e.g., imagery from surface vessels, shore stations, etc.). There is a strong need for robust and efficient methods enabling the automated processing of close-range sea ice imagery to aid in the derivation of useful characteristics of sea ice cover (ice types, concentration, decay).

How accurately can ice objects in close-range optical images be automatically detected and identified to supplement on-ground operations and validate satellite-derived sea-ice products?

Custom-built datasets for training, validation, and testing: 375 unique close-range optical images of ice cover (three channel RGB, jpeg), manually collected, labeled (following ice object definitions and labelling rules), and verified (with an ice expert). 14 classes: Ice objects (*level ice, deformed ice, brash ice, pancake ice, iceberg, floeberg, floebit, floe, broken ice, underwater ice*) and additional features (*shore, water, sky, melt pond*).

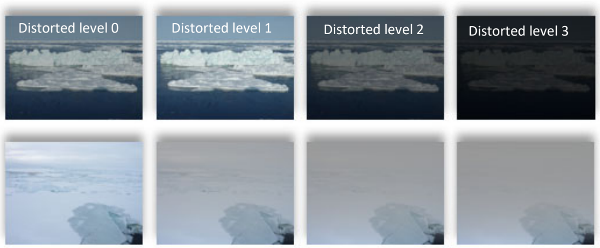
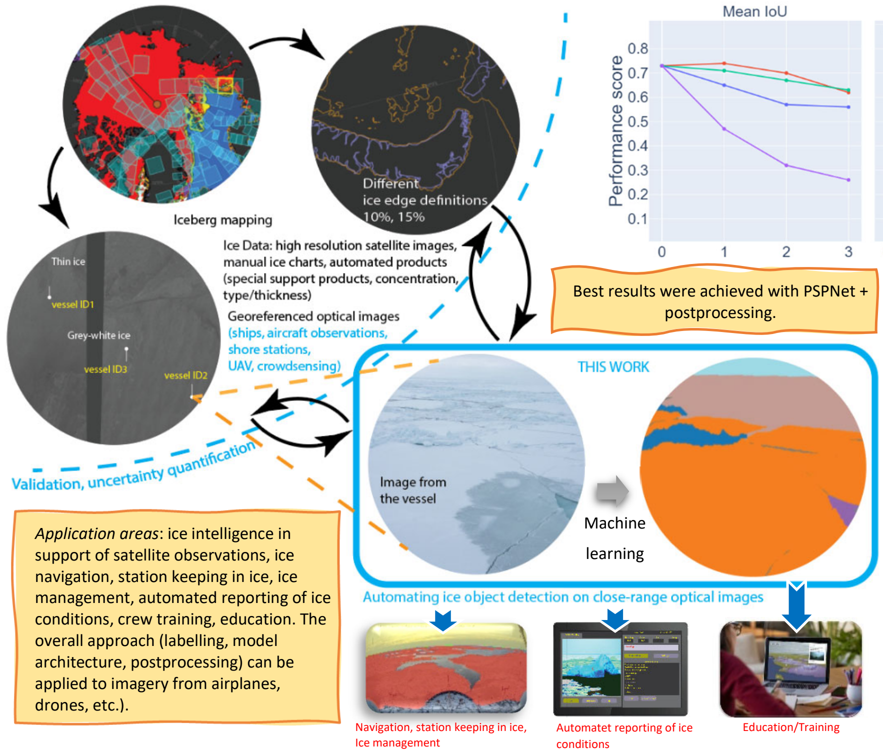


Figure1: Example images (clean images and distorted images with fog and brightness).

Model architecture: Evaluated 12 open-source neural network architectures: PSPNet, PSPDenseNet, DeepLabV3 Plus, UperNet, DUC HDC, FCN, GCN, ENet, UNet, UResNet (UNet with ResNet backbone), SegNet, SegResNet.

Adds-on: Evaluated performance on clean and distorted images (3 distortion levels for fog, dark, blur, noise), with and without postprocessing (fully connected conditional random fields and faster convolutional conditional random fields), various model ensembles, human factors, and compared model predictions with human performance.

Performance metrics: Global and class-wise Accuracy, mean Intersection over Union, Confusion Matrices, F1 score



Application areas: ice intelligence in support of satellite observations, ice navigation, station keeping in ice, ice management, automated reporting of ice conditions, crew training, education. The overall approach (labelling, model architecture, postprocessing) can be applied to imagery from airplanes, drones, etc.).

Results: The initial results from analysis of the model predictions (Figure 2 - below) showed *a relatively good segmentation of clean images, with the mean intersection over union (IoU) of 0.73* (fully convolutional U-Net model with the a pretrained ResNet101 as encoder and convolutional conditional random fields based post-processing of model outputs).

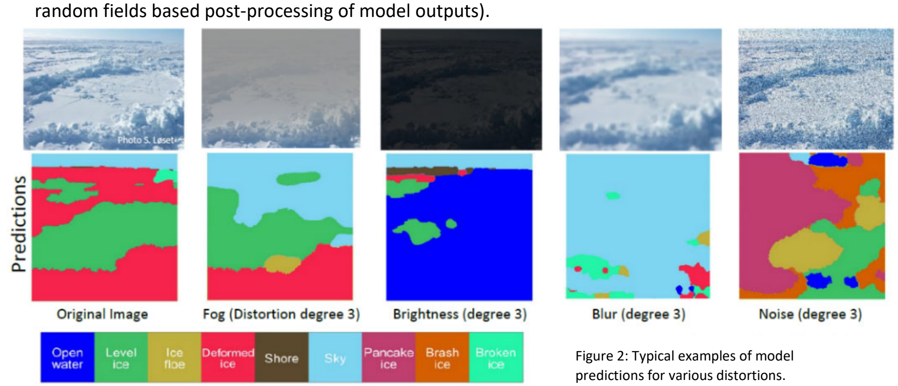


Figure 2: Typical examples of model predictions for various distortions.

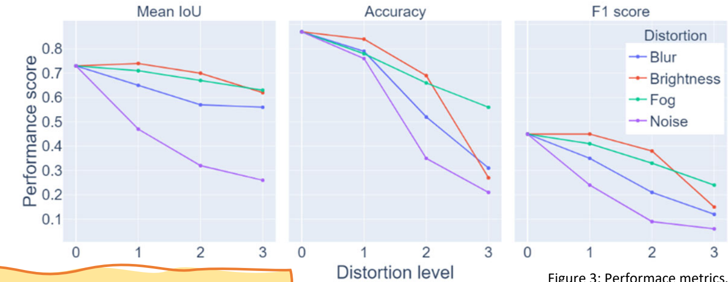


Figure 3: Performace metrics.

Best results were achieved with PSPNet + postprocessing.

We are currently working on improving model performance on distorted images, making it more robust on previously unseen visual conditions. In general, noise distortion has the most profound effect on performance (Figure 3), whereas the fog and darkness affect the predictions least, when the performance is measured in terms of mean IoU.

Remarks: This work opens a possibility for automation of ice object detection and identification from georeferenced close-range optical images (e.g., imagery from surface vessels, shore stations, etc.). The identified and georeferenced ice types that can serve as ground-truth data for validation of satellite-derived ice-cover features.

We have highlighted an area where the current model works and fails, thus giving important indications of where to direct future research efforts.

References:

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