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Trondheim, June 14 to 18, 2020

Real-time classification of the sea ice interacting on a bridge pier using artificial intelligence techniques

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This research focuses on the development of a novel approach for monitoring and classifying different kinds of sea ice interacting with bridge piers in Northumberland Strait. Different ice types can have a varying impact on the navigability of a vessel or the loads on a structure. As such, the ability to monitor and classify different ice types automatically is an added strength to the existing ice load monitoring system present at the Confederation Bridge since 1997 and should allow for further automation. A deep learning algorithm based on Convolutional Neural Networks (CNN) has been utilized for training an algorithm to classify four different types of sea ice interacting with the bridge pier. Despite the fact that classification of different ice types from images is sometimes very challenging even when performed manually by experts, the developed algorithm is able to identify different classes accurately and on a real-time basis. The accuracy of the results demonstrates high practical utility of the method for similar applications.

1. Introduction

Ice loading on the Confederation Bridge has been monitored by the University of Calgary (Brown, 2001, Brown et al., 2010, Shrestha and Brown, 2018) and the NRC (Kubat et al., 2000, and Poirier et al., 2015) since its construction in 1997. This long term data record is the only one of its kind that provides ice loads on structures. The next longest comparable dataset is LOLEIF/STRICE which acquired 4 seasons of ice interactions against the Norströmsgrund lighthouse (Li et al., 2016).

Visual examination of video data from the Confederation Bridge has provided researchers valuable information on the volume and type of ice interacting with the instrumented bridge piers, as well as the ice failure mechanisms. Visual observation is currently the most reliable means of ice characterization. However, this task is challenging, expensive and requires specialized training. New technologies in image processing and computer vision can be applied for this purpose. These would improve automation and reduce the time and effort required to collect these data. Attempts have previously been made for river ice detection and characterization using computer vision algorithms (Ansari *et al.*, 2017); machine learning methods (Kalke and Loewen, 2018) and deep learning techniques (Singh *et al.*, 2019) and (Ansari et al., in prep.). In this study, an automated sea ice characterization algorithm was developed to detect and characterize the sea ice interacting with a bridge pier.

2. Study area and data

Confederation Bridge is the longest structure in the world constructed in ice-covered waters. The Confederation Bridge as part of the Trans-Canada Highway is the 13-kilometre linkage between the provinces of Prince Edward Island and New Brunswick across the Northumberland Strait. This bridge has 45 main spans, each 250 m long, that rest on a total of 44 piers (Poirier, Babaei and Frederking, 2015). Figure 1 illustrates the bridge and its location. As part of a comprehensive ice load monitoring program, two Sony SNC-EB632R cameras are installed to examine ice failures on two of the bridge piers. Cameras are connected to the network, and they are programmed to collect an image every 3 seconds. According to the Canadian Ice Service (CIS) Gulf of St. Lawrence, the ice season in this location is between December 31st to April 15 (Johnston M.E. and Timco, G.W. 2008).

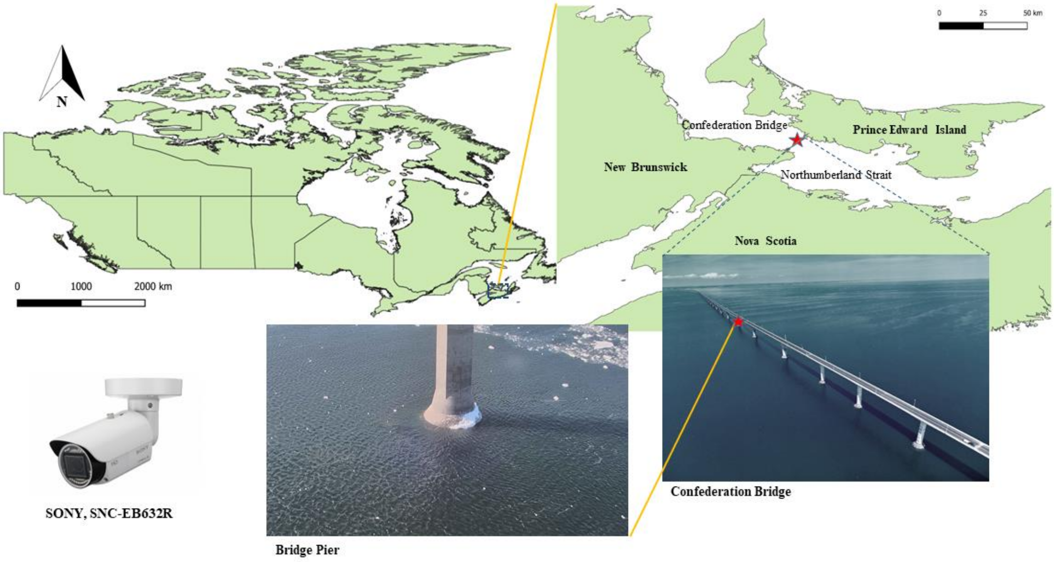
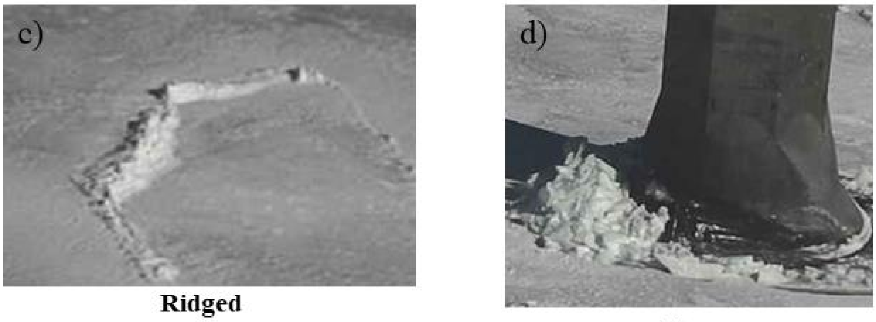


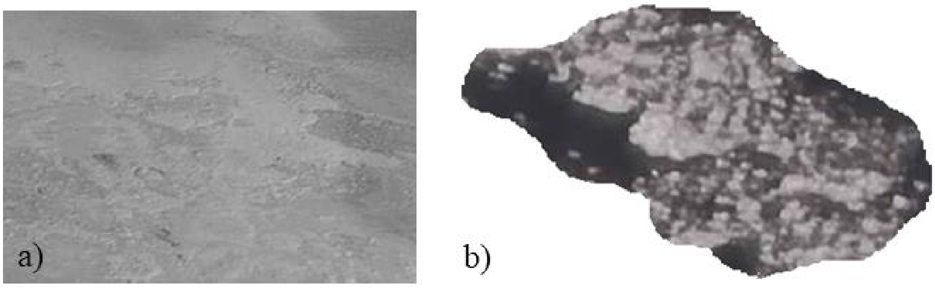
Figure 1. Project location, Confederation Bridge, and the SONY, SNC-EB632R

The vast number of images not only helps in the monitoring task but also provides the possibility of developing data-driven approaches for sea ice characterization. In this study, four different classes of sea ice have been defined for automatic recognition. These classes include *Icefloe, Broken, Ridge,* and *Flex.* The majority of the ice in any given image is ice floe (*Icefloe*). *Icefloe* is generally a piece of level ice that is at least half as large as the pier base, i.e., $\geq$ 5 m in diameter (Figure 2a). An *Icefloe* can also include deformed (ridged or rafted) ice. *Broken* sea ice is considered as the least imposing ice on a vessel or a structure. These are pieces of ice no larger than half of the pier base; in this dataset they are usually broken as a result of interacting with the bridge pier (Figure 2b). Deformed ice (ridged or rafted) is identified as *Ridge* (Figure 2c). Rafted ice occurs when two level ice sheets collide with each other and one is pushed over the other one leading to thickening of ice. Ridged ice, on the other hand, is when levelled ice interacts with an object, causing broken ice pieces to accumulate above or under the ice sheet. Finally, due to the conical shape of the bridge pier, ice interaction with the bridge leads to flexural failure; this is characterized as *Flex* in the presented algorithm (Figure 2d).



Ridged

Flex



Floe

Broken

Figure 2. Different ice type classes; a) Floe; b) Broken ice; c) Ridged; d) Flex

3. Methodology

An instance image segmentation and object detection algorithm was employed to develop a real-time sea ice detection and classification algorithm. Mask RCNN model (He *et al.*, 2017) is the base model to establish the sea ice recognition algorithm. The Mask RCNN model used in this study was built on the Faster RCNN (Ren *et al.*, 2017) model. In the Mask RCNN a convolutional neural network first is used to generate object proposals within the image. An object proposal is essentially a rectangular area within the image that is identified to have a classifiable sea ice object within it. Then the Mask RCNN classifies the bounding boxes and adds an extra mask over the region of interest (RoI) (He *et al.*, 2017) to specify the polygon of the classified sea ice object. The architecture of the used model consists of a feature extraction model using a 101 layer Residual Neural Network (ResNet) (He *et al.*, 2006). After the feature extraction, the Region Proposal Network (RPN) is used to generate the correct RoI. The generated RoIs are then classified using the RoI classification algorithm. In the next step, a bounding box regressor is used for refining the bounding boxes of the classes and another methodology named as RoIAlign based on a bilinear interpolation is used for pixel-wise prediction of the masks (He *et al.*, 2017). Figure 3 illustrates the developed algorithm used for automated classification of the sea ice interacting with the bridge pier.

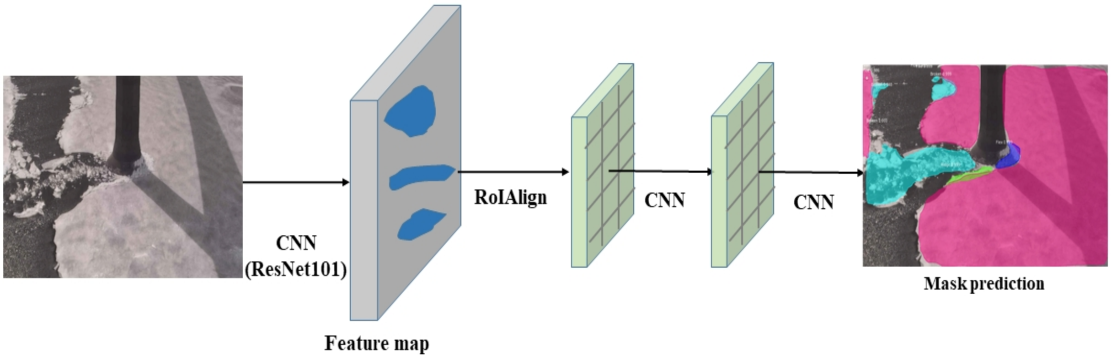


Figure 3. Architecture of the utilized improved version of the Mask RCNN

3.1. Implementation

The developed algorithm utilizes the Mask RCNN model on TensorFlow (Abadi et al. 2015). The training of the model was conducted on a Graphics Processing Unit (GPU) equipped machine. Parallel GPU computing was utilized to accelerate the training process of the model. The training was performed on the backbone structure of ResNet101 (101 layers), with a batch size of 2 images with a training rate of 0.0015 and learning momentum of 0.88 and weight decay of 0.0002. The trained Mask RCNN model was performed on the pre-trained weights of the COCO data (Common Objects in Context) set (Lin *et al.*, 2014). 120 images with the size of 1920 × 1080 were annotated to be used in the training procedure. The image data set was split into 80 percent for training and 20 percent for validation. Moreover, in order to increase the generalization of the algorithm, simple data augmentation techniques such as random flips, left zoom, right zoom were employed in the model. The inference process was also conducted with a detection confidence of 70%.

The utilized model was optimized during the training process to evaluate the accuracy of the model and the sufficient number of the annotated images for the training process. The training process was performed with 100 epochs.

4. Results and discussion

After the investigation of the loss and validation parameters, the results indicate that validation loss values quickly reach their lowest after a few ephochs and then continue to fluctuate. However, training loss values continue to decend. This suggests that the model memorizes before the 20th epoch. Thus running the model for the 100 epochs does not give any advantage. Based on the validation loss increase no more than 20 epochs should be utilized, because otherwise the model is overfit to the training data-set. The reason for this is that the training process has been conducted on a weighted data set as a result of pertaining COCO dataset. Moreover, this is an indication of the insufficiency of the labelled images for the training process.

Figure 4 shows some results of the sea ice characterization algorithm. Four different classes of floe, broken, flex, and ridge have been detected. The detected ice types have been segmented with masks and their associated colors. The results show that the developed algorithm was able to detect, identify and characterize the four different classes accurately and with acceptable pixel-wise accuracy. While the results are promising, two sets of errors were discovered. Although the classification and detection tasks were conducted correctly the mask prediction has some errors. The errors include the marginal error in the boundaries of the masks and some overlaps in the mask prediction pixels. As this was predictable from the loss graphs in the optimization process, there is still a need to perform the manual labelling task on a greater number of images to ensure the reliability of the system.

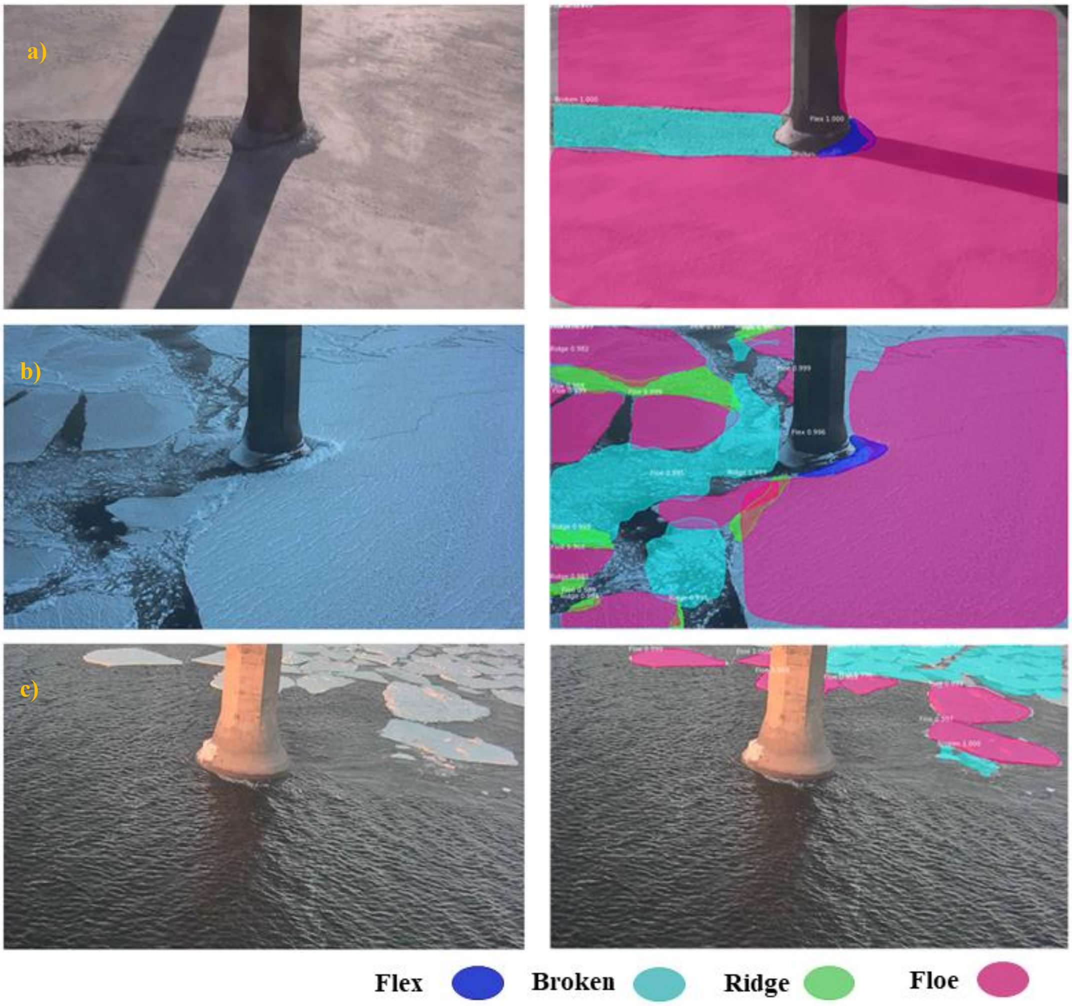


Figure 4. Sample results of the sea ice segmentation algorithm

5. Conclusion

As part of a comprehensive and automated monitoring network a sea ice characterization algorithm was developed to detect and recognize different classes of ice interacting with a bridge pier. With a changing climate, results of such a study are crucial, since monitoring, and specifically automated smart monitoring, is vital in providing the public with high-standard safe and reliable infrastructure. The developed algorithm employed an improved version of the Mask RCNN to improve sea ice characterization. The results indicated an acceptable outcome with some minor shortcomings, which should be investigated in future studies. Annotation of more images is a key factor in the generalization of the developed algorithm, which should be conducted in future work.

6. Acknowledgments

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