Small Vessel Detection from Synthetic Aperture Radar (SAR) Imagery using Improved Deep Learning

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1 Group Members

We both plan to work on all sub-tasks together. Here is the schedule for the project sub tasks:

1. Basic data processing on provided set and additional data (first week)

2. Build and fine-tune language models (week 2 - week)

4. Apply model enhancements (Faster R CNN) and advanced augmentation techniques (ex: random rotation) (week 4)

5. Performance analysis and model/data fine-tuning (week 5)

6. Write the final report (week 6)

2 Motivation

The motivation for this project comes from the fact that Image classification on large objects is widely explored area compared to low resolution small objects on a large background. One such problem is detecting small vessels from Synthetic Aperture Radar imagery. Some ship targets and non-ship targets such as waves, dams, islands, icebergs, or reefs, have approximate back-scattering intensity in SAR imagery that makes ship detection in SAR imagery difficult, making this problem one of the many unsolved problems in computer vision literature.

3 Literature Review

A prelimnary literature review shows authors using YOLO, Masked RCNN (He et al., 2018), Retina Nets (Lin et al., 2017), Faster RCNN (Ren et al., 2015), (Tong et al., 2020) to solve the problem. (Kanjir et al., 2018) highlights the challenges faced when trying to improve detection of inshore object detection. So we plan to use Faster R-CNN (Ren et al., 2015) and ResNets (Lin et al., 2017) as mentioned in (Zhang et al., 2020). are referring to data augmentation techniques for small object detection, multi scale feature learning (Hu et al., 2018) , land masking strategies (An et al., 2018), Bathymetry (Sagawa et al., 2019) and hyper parameter tuning to further improve the model.

4 Approach

Our goal is to achieve maximal performance on the data-set. Therefore, we intend to experiment with a variety of techniques to create a robust classifier. Broadly, our techniques will fall under expanding our training set similar to the ideas of data augmentation, and model fine-tuning. However, first we will implement 2 of the baselines that are described in (Y.Wu et al., 2019) (Carion et al., 2020) Facebook's Detectron2 API. We will use (1) Faster Region-Based Convolutional Neural Network (Faster R-CNN) (Ren et al., 2015) (2) RetinaNet (Lin et al., 2017) both pre-trained on the COCO dataset as our Neural Net Architecture. For both of these models, we will use ResNet-50 with Feature Pyramid Network (FPN) pre-trained on the ImageNet dataset as the backbone (He et al., 2016). We will add a Validation Set, Learning Rate Scheduling, and ResNext to improve the performance.

5 Data

We will use the Large-Scale SAR Ship Detection Dataset-v1.0 (LS-SSDD-v1.0) (Zhang et al., 2020) from Sentinel-1 [1]. LS-SSDD-v1.0 contains 15 large-scale 24,000 × 16,000 pixel, SAR images. The original large-scale SAR images are cut into 9000, 800×800 pixel sub-images. The authors use the first 10 of the 15, large-scale images as the training set (train). The last 5, large-scale images are used as the test set (test). test is further broken down into 2234 offshore sub-images (test offshore) and 766 inshore sub-images (test inshore). We will experiment with incorporating other datasets into our existing training set. Related datasets that may give us additional information for training include:

HRSID: This dataset was created to reduce wrong annotation and missing annotation, and used optical remote sensing imageries to reduce the interferes from harbor constructions. (Wei et al., 2020).

6 Evaluation Metrics

The following evaluation metrics are considered on test: Detection Probability (Pd), False Alarm (Pf), Missed Detection (Pm), Recall, Precision, Mean Average Precision (mAP), and F1 score. To compare the baseline model results with further modelings, only mAP is used as a single evaluation metric

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