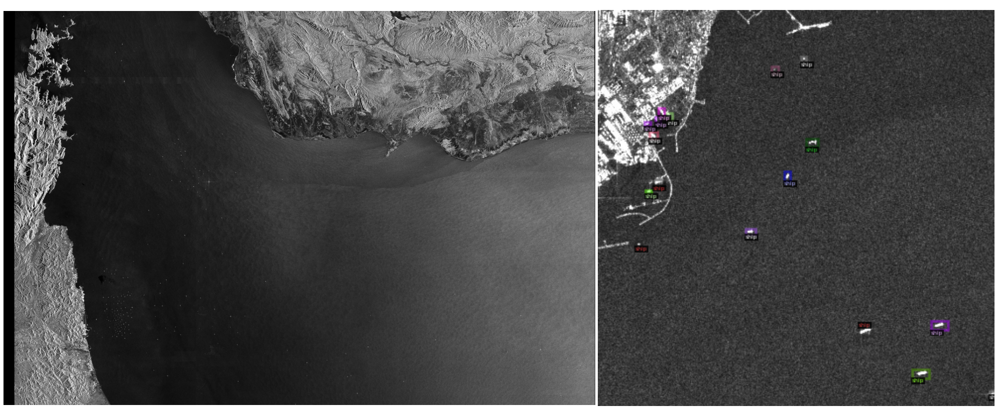
Small Vessel Detection from Synthetic Aperture Radar (SAR) Imagery using Deep Learning
(Application Project - Computer Vision)

Jake Taylor
jakee417@stanford.edu

Toktam Mohammadnejad
toktammd@stanford.edu

1 Description

Synthetic aperture radar (SAR) provides high-resolution, all-day, all-weather satellite imagery, which has become one of the most important means for high-resolution ocean observation and is well suited to better understand the maritime domain. We propose using the LS-SSDD-v1.0 open source SAR dataset to build and train a computer vision small vessel detection model which automatically generates bounding boxes around maritime vessels [1]. This type of automation would allow regulatory agencies to better conduct shipwreck rescue, fishery enforcement, and vessel traffic management.



(a) Large Scale Image (24,000 × 16,000 pixels) (b) Clipped Training Image (800 x 800 pixels)

Figure 1: Comparison of LS-SSDD-v1.0 SAR large scale image and clipped training image containing detected maritime vessels.

2 Challenges

Object detection from SAR imagery is challenging for a variety of reasons. Some ship targets and inshore non-ship targets such as waves, dams, islands, or reefs, have approximate backscattering intensity in SAR imagery that makes ship detection in SAR imagery difficult. Moreover, many low-level and mid-level image features that have been widely used in object detection and classification applications cannot be introduced directly into ship detection via SAR imagery, which imposes an additional challenge. Lastly, detecting small objects in large-scale remote sensing images remains an unsolved problem within the computer vision community.

3 Dataset

We use the Large-Scale SAR Ship Detection Dataset-v1.0 (LS-SSDD-v1.0) from Sentinel-1 [1]. LS-SSDD-v1.0 contains 15 raw, large-scale, space-borne, 24,000 × 16,000 pixel, SAR images. To facilitate network training, the original large-scale SAR images are directly cut into 9000, 800×800 pixel sub-images. As a result, 600 sub-images are obtained from each large-scale SAR image. Cumulatively, a total of 9000 sub-images are generated for network training and testing in the LS-SSDD-v1.0 dataset [1]. In addition, data augmentation (e.g., image flipping, contrast enhancement, random scaling) will be utilized to increase the overall size of the training dataset.

4 Learning Method

We will utilize convolutional neural networks (CNNs) in order to extract information at different levels of abstraction from the SAR imagery and detect small ships in the large-scale SAR images. We have implemented different CNN architectures as baseline models, like Faster R-CNN [2], RetinaNet [3] and so on, and will now compare the performance of these methods on large-scale SAR images in terms of both detection accuracy and detection speed. The speed of ship detection in SAR images is particularly important in real-time applications, such as search and rescue in maritime emergency [4; 5; 6]. Implementation of these baseline models came from Facebook's Detectron2 API, an open source detection toolbox [7; 8]. After these baselines are evaluated, we will try to implement more advanced data augmentation, sea-land masking, and more complex model architectures to improve overall performance.

5 Related Work

A survey of works related to deep learning-based object detection is shown in [9]. A survey specific to small object detection is shown in [10]. This project will specifically rely on the dataset and benchmark results given by [1] which has related research in [4; 5; 6]. Finally, data augmentation approaches related to small object detection can be found in [11].

6 Evaluation

To discern between vessel and non-vessel, a score threshold of 0.5 will be used. To compare model output against ground truth bounding boxes, a 50% intersection over union (IOU) will be enforced. Finally, a variety of evaluation metrics will be used on an unseen test set to gauge the quality of the model output: Detection Probability (P_d), False Alarm (P_f), Missed Detection (P_m), Recall, Precision, Mean Average Precision (mAP), and F1.

References

[1] T. Zhang, X. Zhang, X. Ke, X. Zhan, J. Shi, S. Wei, D. Pan, J. Li, H. Su, Y. Zhou, and D. Kumar, "Ls-ssdd-v1.0: A deep learning dataset dedicated to small ship detection from large-scale sentinel-1 sar images," *Remote Sensing*, 2020.

[2] S. Ren, K. He, R. B. Girshick, and J. Sun, "Faster R-CNN: towards real-time object detection with region proposal networks," *CoRR*, vol. abs/1506.01497, 2015.

[3] T.-Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollár, "Focal loss for dense object detection," 2018.

[4] T. Zhang and X. Zhang, "High-speed ship detection in sar images based on a grid convolutional neural network," *Remote Sensing*, vol. 11(10), 2019.

[5] T. Zhang, X. Zhang, J. Shi, and S. Wei, "Hyperli-net: A hyper-light deep learning network for high-accurate and high-speed ship detection from synthetic aperture radar imagery," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 167, pp. 123 – 153, 2020.

[6] T. Zhang and X. Zhang, "Shipdenet-20: An only 20 convolution layers and <1-mb lightweight sar ship detector," *IEEE Geoscience and Remote Sensing Letters*, pp. 1–5, 2020.

[7] Y. Wu, A. Kirillov, F. Massa, W.-Y. Lo, and R. Girshick, "Detectron2." `https://github.com/facebookresearch/detectron2`, 2019.

[8] N. Carion, F. Massa, G. Synnaeve, N. Usunier, A. Kirillov, and S. Zagoruyko, "End-to-end object detection with transformers," 2020.

[9] L. Jiao, F. Zhang, F. Liu, S. Yang, L. Li, Z. Feng, and R. Qu, "A survey of deep learning-based object detection," *CoRR*, vol. abs/1907.09408, 2019.

[10] K. Tong, Y. Wu, and F. Zhou, "Recent advances in small object detection based on deep learning: A review," *Image and Vision Computing*, vol. 97, p. 103910, 2020.

[11] M. Kisantal, Z. Wojna, J. Murawski, J. Naruniec, and K. Cho, "Augmentation for small object detection," *CoRR*, vol. abs/1902.07296, 2019.

[12] Z. Cai and N. Vasconcelos, "Cascade R-CNN: delving into high quality object detection," *CoRR*, vol. abs/1712.00726, 2017.

[13] J. S. Z. X. H. F. Jiangmiao Pang, Cong Li, "R2-cnn: Fast tiny object detection in large-scale remote sensing images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 57, pp. 5512 – 5524, 2019.

[14] K. Chen, J. Wang, J. Pang, Y. Cao, Y. Xiong, X. Li, S. Sun, W. Feng, Z. Liu, J. Xu, Z. Zhang, D. Cheng, C. Zhu, T. Cheng, Q. Zhao, B. Li, X. Lu, R. Zhu, Y. Wu, J. Dai, J. Wang, J. Shi, W. Ouyang, C. C. Loy, and D. Lin, "Mmdetection: Open mmlab detection toolbox and benchmark," *CoRR*, vol. abs/1906.07155, 2019.