SMARTSAT COOPERATIVE RESEARCH CENTRE

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Semi-Supervised Learning for Automatic Improvement of Onboard Object Detection Models on Small Satellites

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Introduction

- The development of edge computing platforms (*e.g.*, NVIDIA Jetson, Intel Movidius Myriad, and Google Coral) and strategies to minimize the cost of executing neural networks (SZE et al., 2017) can considerably improve onboard image processing in nanosatellites, such as CubeSats
- Benefits include reducing bandwidth usage, reducing power consumption, and prioritizing images to downlinking
- Current approaches implement image classification for cloud detection (GIUFFRIDA et al., 2020) and image segmentation for flood mapping (MATEO-GARCIA et al., 2021)
- Existing approaches have some limitations, such as using a static detection model, ignoring images not selected for downlinking (possibly false negatives), and potentially causing sample bias

Methods

- There are different options to allow automatic onboard improvement
- Supervised learning is not a viable solution since it requires using only labeled images, and labeling demands high bandwidth usage to transmit images to the ground and high manual effort to label them
- Weakly semi-supervised learning also faces similar challenges given that it relies on image-level labels
- Semi-supervised learning employs unlabeled images to improve the detection performance of a supervised baseline
- A few labeled images can be acquired via active learning

(a) (b) (c)

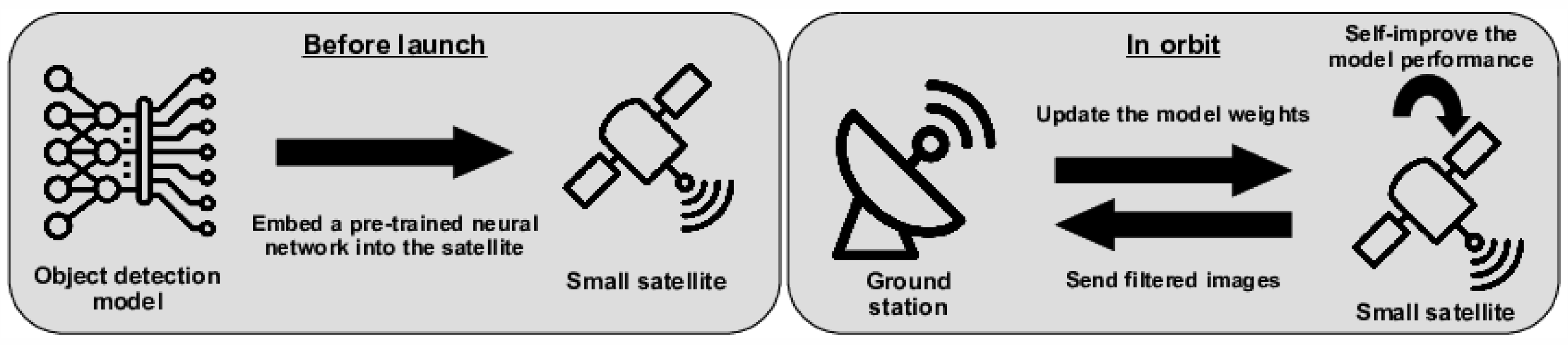
Different types of image labels for object detection: (a) box-level, (b) image-level, and (c) fully unlabeled. Images from (AIRBUS, 2018).

Challenges

- Various approaches exist for semi-supervised object detection (SSOD), including pseudo-labeling, data distillation, consistency regularization, mean teacher, and other ensemble methods
- These methods boost the detection performance (mAP) using unlabeled data, but they make training more complex due to additional computation
- Nanosatellite hardware has severe restrictions in power, processing, and memory, which pose a major constraint to performing onboard training

Objectives

- This research aims to develop efficient SSOD methods suited for deployment on nanosatellites, considering their specific limitations
- We will perform experiments to validate our SSOD solutions with satellite imagery datasets (*e.g.*, for ship detection) and a CubeSat testbed



The pipeline for self-improvement of an object detection model in orbit.

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AusIndustry Cooperative Research Centres Program