Automatic Satellite Characterization using Simulated ISAR data

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ABSTRACT

Space domain awareness has gained traction in recent years, encompassing the charting and cataloging of space objects, anticipating orbital paths, and keeping track of re-entering objects. Radar techniques can be used to monitor the fast-growing population of satellites, but so far this is mainly used for detection and tracking. For the characterization of a satellite's capabilities, more detailed information, such as inverse synthetic-aperture radar (ISAR) imaging, is needed. Deep learning has become the preferred method for automated image analysis in various applications. Development of deep learning models typically requires large amounts of training data, but recent studies have shown that synthetic data can be used as an alternative in combination with domain adaption techniques to overcome the domain gap between synthetic and real data.

In this study, we present a deep learning-based methodology for automated segmentation of the satellite's bus and solar panels in ISAR images. We first train a segmentation model using thousands of fast simulated ISAR images and then we finetune the model using a domain adaptation technique that only requires a few samples of the target domain. As a proof of concept, we use a small set of high fidelity simulated ISAR images closely resembling real ISAR images as the target domain. Our proof of concept demonstrates that this domain adaptation technique effectively bridges the domain gap between the training and target radar image domains. Consequently, fast simulated (low fidelity) synthetic datasets are proven to be invaluable for training segmentation models for ISAR images, especially when combined with domain adaptation techniques.

Keywords: Deep learning; ISAR; Synthetic data; Domain adaptation; Few-shot learning; SDA; SSA

1. INTRODUCTION

The topic of space domain awareness has gained traction in recent years, encompassing the charting and cataloging of space objects, anticipating orbital paths and keeping track of re-entering objects, and providing data for future anti-satellite weapons systems. Radar techniques take up a key role in space domain awareness as they can be used to monitor the fast-growing population of satellites.[1] So far, radar technology is mainly used for detection and tracking, but to enhance our understanding of the space domain, it is necessary to characterize satellites beyond their position and track.

For the characterization of a satellite's capabilities, more detailed information can be retrieved with techniques such as inverse synthetic-aperture radar (ISAR). With ISAR, the movement of the target is used to create a synthetic aperture, creating a detailed image of the satellite's reflective properties. Large-scale deployment of ISAR to keep track of space objects necessitates the processing of large quantities of image data, which for effective analysis, requires automated and near-real time image analysis.

Deep learning[2] has become the preferred method for automated image analysis in various applications, including robotics,[3] medical image analysis,[4] military object detection,[5] and satellite imagery analysis.[6] Recent work has also shown the potential for space domain awareness, for example, for the localization and classification of space objects in RGB and depth images.[7]

Development of deep learning models typically requires large amounts of training data, which can be difficult and expensive to acquire, but recent studies have shown that synthetic data has the potential to be used as an alternative. Specifically on the topic of ISAR image analysis, van Rooij et al.,[8] showed that satellites can be

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Synthetic Data for Artificial Intelligence and Machine Learning: Tools, Techniques, and Applications II, edited by
Kimberly E. Manser, Christopher L. Howell, Raghuveer M. Rao, Celso De Melo, Proc. of SPIE
Vol. 13035, 1303517 © 2024 SPIE · 0277-786X · doi: 10.1117/12.3013381

accurately segmented in fast-simulated ISAR images. From the segmentations of the satellite's bus and solar panels, some key characteristics can be inferred, including the size and orientation of these substructures. Despite these promising results, a deep learning model developed with data from a simulator does not necessarily perform well on real data, or even on synthetic data that is created with a different simulator.

This domain gap, which describes the gap in performance between images from the source domain and target domain, follows from the difference in appearance between the data sets, in combination with the tendency of a deep learning model to learn shortcuts that are mostly applicable to the source domain. Various techniques have been proposed to overcome the domain gap, for example by increasing the variation in the simulations of the source domain.[9] Another strategy is to make use of domain alignment techniques where a small number of images from the target domain is used to adapt the deep learning model to the data distribution of the target domain.

In recent work, we employed a few-shot domain alignment method to finetune a segmentation model -initially trained on fast-simulated images- with only four images of high-fidelity simulated ISAR images.[10] We achieve good segmentation performance, even though appearance of the high-fidelity simulated ISAR images (target domain) is quite different than the images of the source domain, and includes strong image artifacts that are also typical of acquired ISAR data. In this paper, we summarize our latest results.

2. METHODS

Figure 1 shows an overview of our methods. We first train a deep learning-based segmentation model using thousands of fast simulated ISAR images of the Envisat satellite. This baseline model outputs a probability map for each of the classes background, bus, and solar panel. The baseline model is then fine-tuned using only four high-fidelity simulated ISAR images of Envisat. The high-fidelity simulations include propagation losses, thermal noise, 3D-mesh models of satellites for RCS modeling, real orbits, and acquisition errors. These images are computationally expensive to generate, but closely resemble real ISAR images. For more details about both image sets and annotations we refer the reader to Heslinga et al.[10] For the fine-tuning we make use of a few-shot learning method for semantic segmentation by Tavera et al. called Pixel-By-Pixel Cross-Domain Alignment (PixDA).[11] The method includes a pixel-by-pixel domain adversarial loss that was designed to align the images of the source to the target domain on a pixel-level.

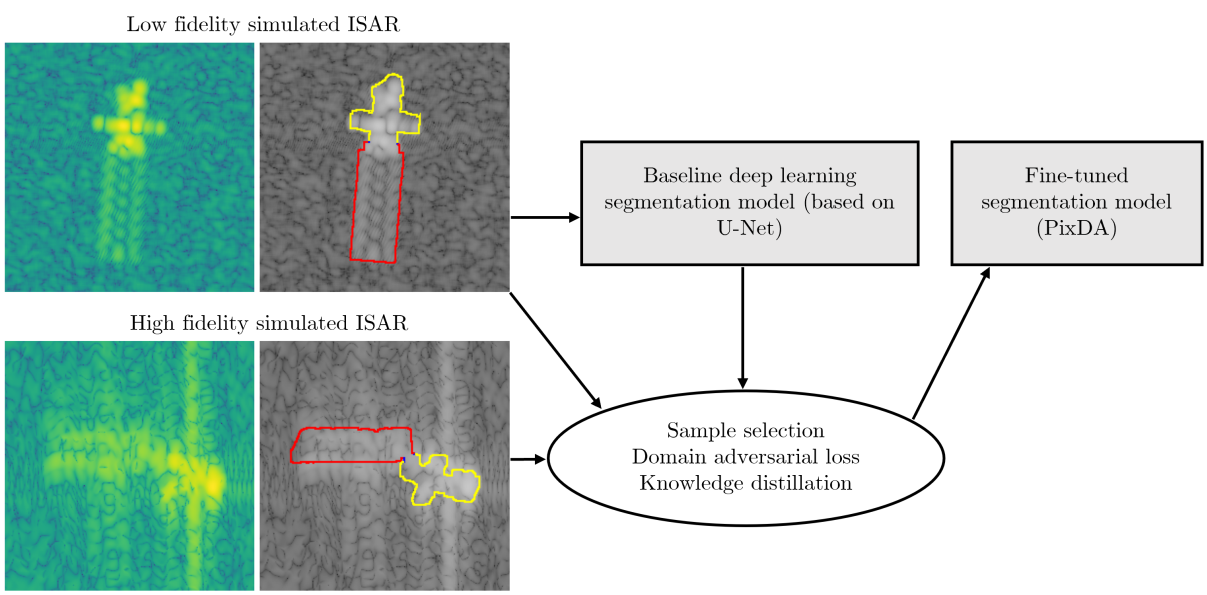

Figure 1: Overview of our method for few-shot learning for satellite segmentation in synthetic ISAR images.

We evaluate the baseline model and fine-tuned model by processing images that were not used for model development. The metric for evaluation is Intersection over Union (IoU), which we calculate for the bus class and solar panel class.

3. RESULTS

When the baseline model is applied to the fast simulated ISAR images in the evaluation set, the result is an Intersection over Union (IoU) of 0.72 ($\pm$ 0.14), where $\pm$ represent one standard deviation. The top row of Figure 2 shows an example where the predicted segmentations are very close to the ground truth mask of a fast simulated ISAR image. However, when this baseline model is applied to the high fidelity simulated ISAR images, the resulting segmentations are poor (IoU = 0.13 $\pm$ 0.04). An example of this is shown in the second row of Figure 2, where the baseline prediction is clearly incorrect. Instead, if the fine-tuned model is applied to this image, the segmentations improve significantly. Across all high fidelity simulated ISAR images, the IoU increases to 0.55 ($\pm$ 0.06).

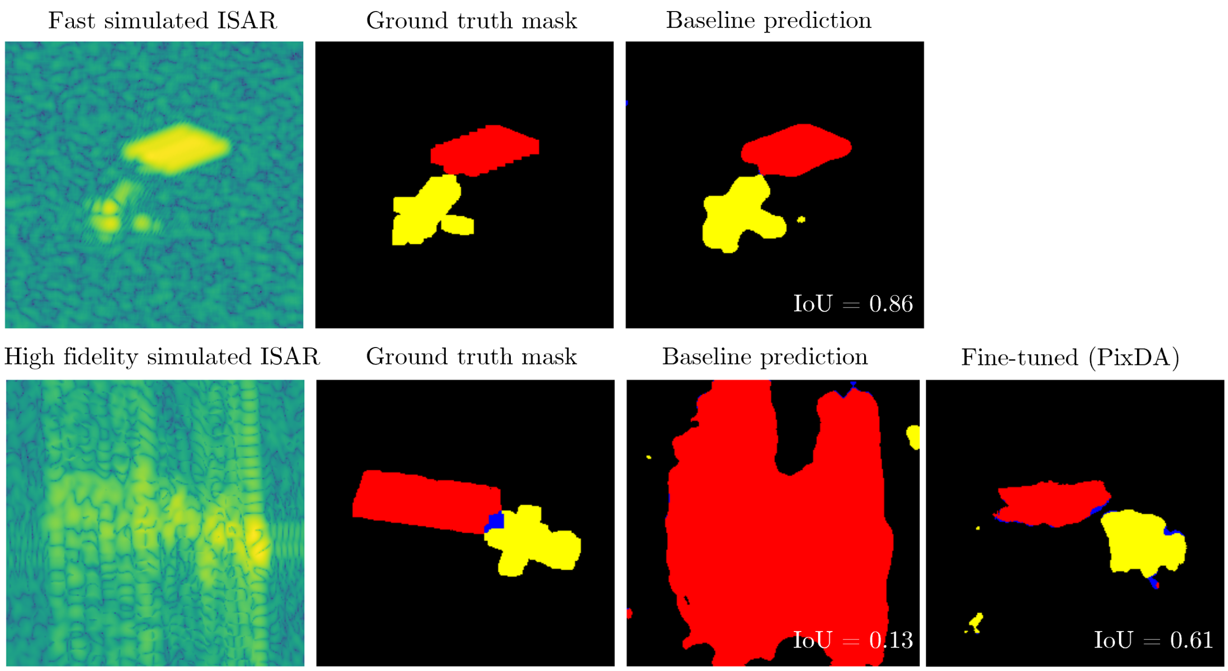

Figure 2: Segmentation results. The top row shows a fast simulated ISAR image and corresponding ground truth mask for the satellite's bus and solar panels. The baseline prediction represents the output of the baseline model. The bottom row shows a high-fidelity simulated ISAR image, with corresponding mask and baseline prediction. For this image, we also show the output of the fine-tuned segmentation model. IoU = Intersection over Union.

4. DISCUSSION

In this study, we showed that a deep learning-based segmentation model can be trained to segment satellite substructures in ISAR images when only a small number of images of the target domain is available. By priming the model on a large set of fast simulated images, and employing a few-shot learning technique, only a small set of high-fidelity simulated ISAR images is needed to obtain useful segmentations. Although we demonstrate the benefits of domain adaptation by using high fidelity simulations, the concept can similarly be applied to measured ISAR images. In future work we are interested in extending our methods to work for several satellites.

Although the obtained segmentations are not perfect, they do allow for characterization of the satellite, including estimating the size and shape of the solar panel and bus, and the satellite's orientation. These results are in line with our objectives for space domain awareness, where we are interested in more than just the detection and orbit estimation of satellites.

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