

Domain Adaptation in Object Detection

In object detection, there are several approaches for targeting a domain gap. Techniques based on feature learning, adversarial style-transfer, semi-supervised learning or graph-neural-networks are popular. We propose to combine style-transfer for input image domain adaptation with semi-supervised learning for object detection network domain adaptation.

Our contributions are:

- We propose **AWADA [2]**, a style-transfer method for domain adaptation for object detection on the input level.
- Additionally, we propose **AST-SSL [1]** combining Semi-Supervised Domain adaptation with AWADA-based adversarial style-transfer [2].

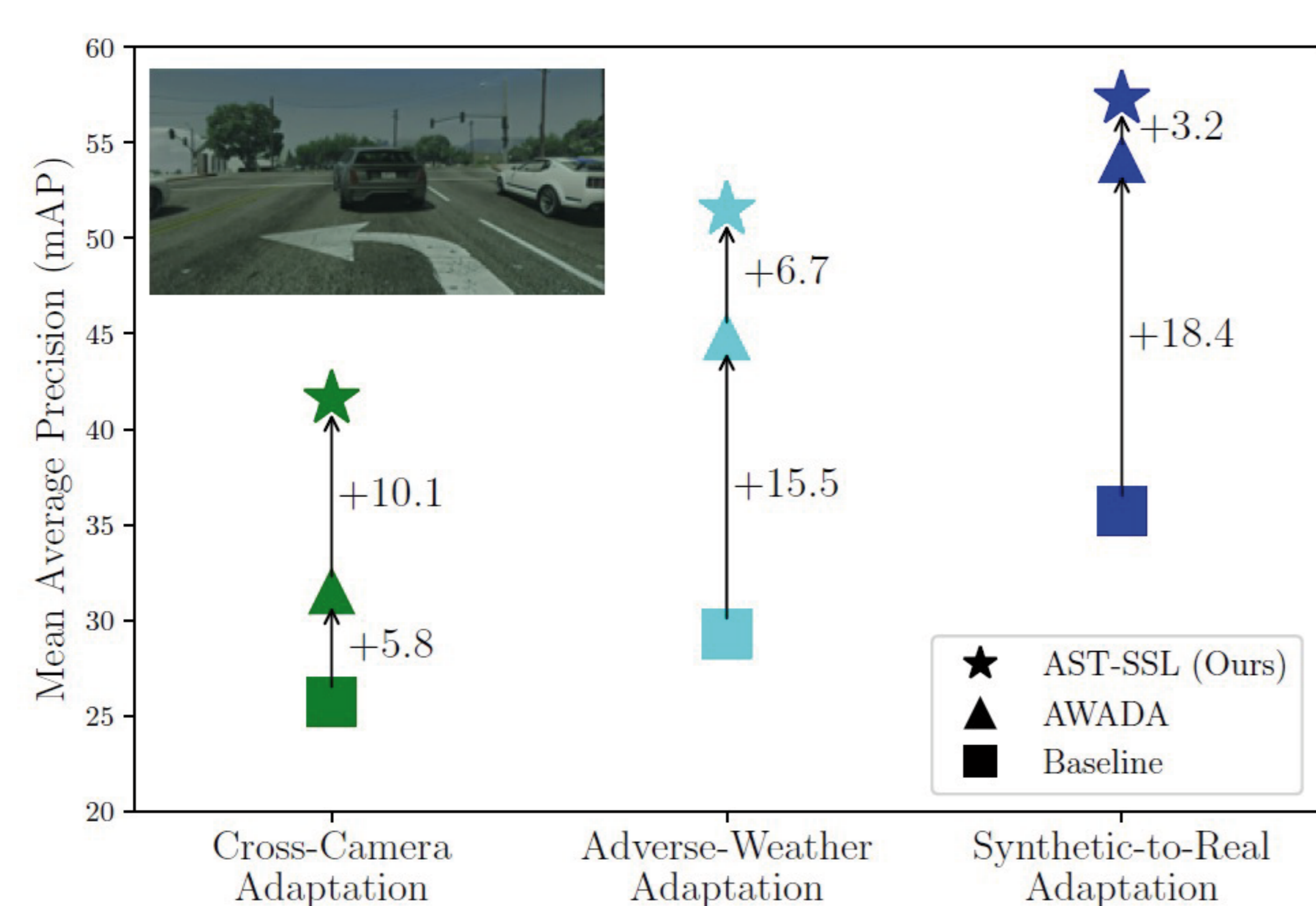


Figure 1: Domain adaptive object detection results on the Cross-Camera, Adverse Weather, and Synthetic-to-Real benchmark.

Figure 1 shows training performances of AST-SSL (Star), which outperform AWADA style-transfer by a huge margin. Especially for cross-camera adaptation the performance gain is >10% due to the large domain gap between source and target domain.

AST-SSL Framework

Our developed AST-SSL framework in Figure 2 consists of a frozen AWADA style-transfer network for aligning source and target domain on the image level.

In addition, AST-SSL applies semi-supervised learning using a student-teacher training paradigm for modifying the object detector training using pseudo-label creating for the target domain.

Therefore, without having access to target domain labels, AST-SSL can have a mixed-training paradigm benefiting from target domain information during training. Strong augmentation (Flipping, Color Jitter, Greyscaling, Gaussian Blur, Erasing and Resize Jitter) additionally supports the semi-supervised object detector training by generalizing to domain invariant feature maps.

Overview

In summary, we propose AST-SSL, combining style-transfer with semi-supervised learning, targeting the domain gap on multiple levels for domain adaptation.

In experiments we can show, that AST-SSL outperforms current state-of-the-art domain adaptive object detection methods by a huge margin on common cross-camera, adverse weather and synthetic-to-real adaptation benchmarks.

References:

- [1] M. Menke, T. Wenzel and A. Schwung, "Improving Cross-Domain Semi-Supervised Object Detection with Adversarial Domain Adaptation," 2023 IEEE Intelligent Vehicles Symposium (IV), Anchorage, AK, USA, 2023, pp. 1-7, doi: 10.1109/IV55152.2023.10186678.
- [2] Menke, Maximilian and Wenzel, Thomas and Schwung, Andreas, Awada: Foreground-Focused Adversarial Learning for Cross-Domain Object Detection. Available at SSRN: <https://ssrn.com/abstract=4272713> or <http://dx.doi.org/10.2139/ssrn.4272713>

AWADA Style-Transfer + Semi-Supervised Learning (AST-SSL) Domain Adaptation for Object Detection

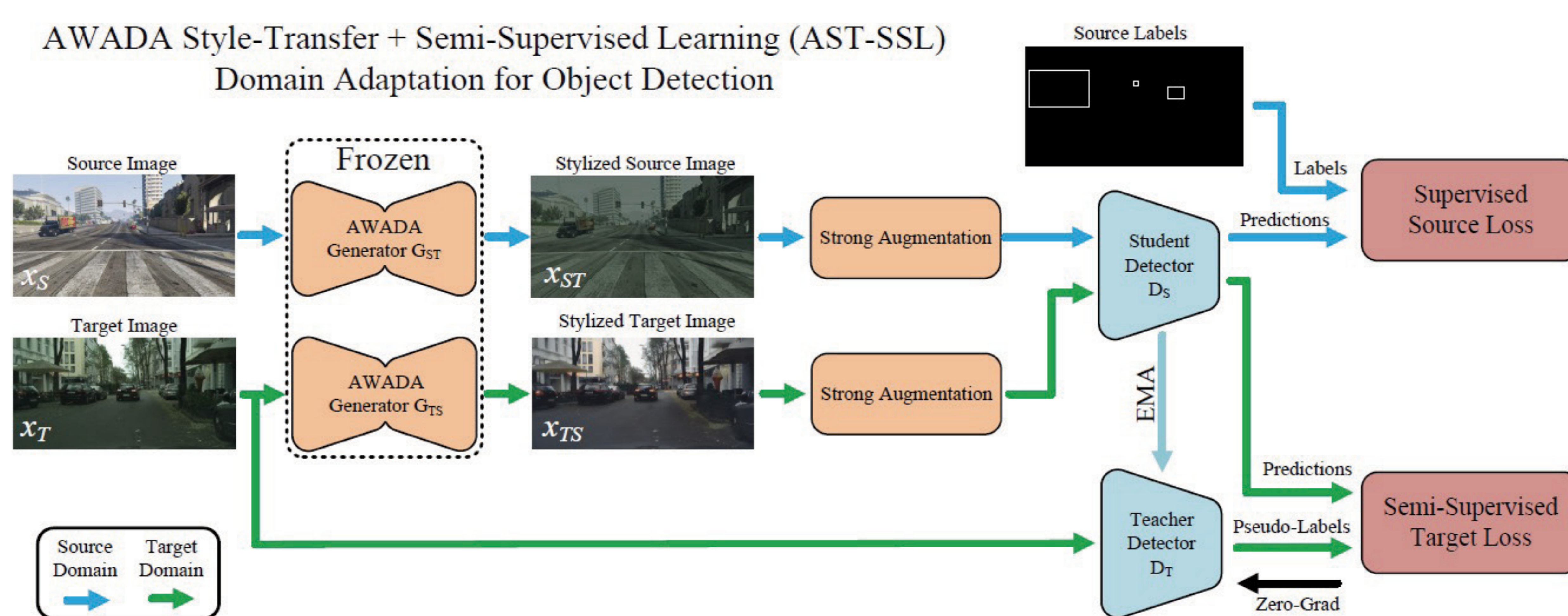


Figure 2: Framework of AST-SSL (AWADA Style-Transfer + Semi-Supervised Learning) with combining adverse style-transfer on the input level combined with semi-supervised learning for generating pseudo-labels for unlabeled target domain images.

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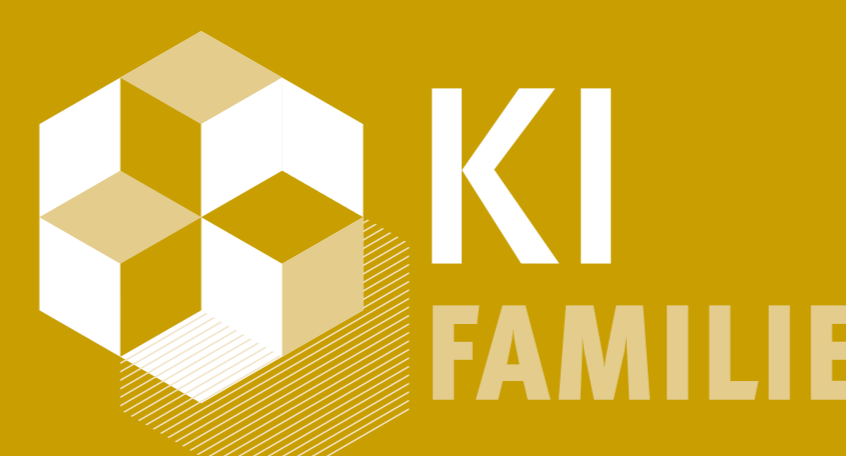


For more information contact:

Maximilian.Menke@de.bosch.com

Maarten.Bieshaar@de.bosch.com

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