

# An Unsupervised Domain Adaptive Approach for Multimodal 2D Object Detection in Adverse Weather Conditions

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## Introduction

While deep learning architectures that fuse vision and range data for 2D object detection have thrived in recent years, the corresponding modalities can degrade in adverse weather or lighting conditions, ultimately leading to a drop in performance. Although domain adaptation methods attempt to bridge the domain gap between source and target domains, they do not readily extend to heterogeneous data distributions.

## Motivation:

Can multimodal methods generalize better than unimodal methods on new domains? And what is the key to accomplish this?

## Contribution:

We leverage different uncertainty concepts to align the source and target foreground features.

## Method

We propose a new framework for multimodal domain adaptation with 4 contributions:

- We propose new data augmentation tools for lidar depthmaps: points dropout, additive point gaussian noise, point scatter.
- We propose to leverage the sensors aleatoric uncertainty to weigh the foreground regions in the network's deep features in order to align them using a domain discriminator.
- We propose self-supervision techniques using geometric transformations on the patch-level. The self-supervised tasks in the target domain are learned in parallel with the detection task on the source domain.
- We leverage the epistemic uncertainty of the network post NMS to filter the predictions of the network. Then, we use these predicted bounding boxes as labels for a teacher student, in a mean-teacher paradigm
- Extension to multi-target DA.

## Results

We show that multimodal DA can outperform state-of-the-art image only DA methods.

Configuration	Clear Day			Light Fog Day			Dense Fog Day			Snow Day			Clear Night			Mean
	Car	Ped.	RV	Car	Ped.	RV	Car	Ped.	RV	Car	Ped.	RV	Car	Ped.	RV	
<b>A</b> Entropy Fusion [16]	81.8	74.8	69.8	84.0	38.2	5.8	71.2	50.0	11.3	78.0	78.4	20.8	59.3	63.4	22.7	48.0
<b>B</b> + Max Entropy	81.6	75.3	69.3	85.1	40.6	5.0	72.2	55.0	<b>14.8</b>	78.4	76.9	13.1	59.3	62.8	27.0	48.4
<b>C</b> + Augmentations	82.5	75.9	69.6	82.7	45.2	<b>5.8</b>	72.7	58.6	13.7	78.6	<b>78.7</b>	13.2	57.6	62.4	25.3	48.5
<b>D</b> + Discriminator	81.0	74.0	69.4	85.4	42.6	1.6	<b>81.7</b>	60.1	14.4	79.1	77.5	21.1	65.5	65.9	30.5	51.8
<b>E</b> + SSL	<b>82.7</b>	76.2	<b>74.4</b>	86.1	44.4	3.3	76.6	59.3	13.7	<b>81.0</b>	<b>78.7</b>	<b>21.5</b>	<b>68.8</b>	<b>67.6</b>	34.8	53.2
<b>F</b> + Domain Balanced	<b>82.7</b>	<b>76.3</b>	72.3	<b>86.8</b>	<b>51.0</b>	2.7	77.4	<b>61.8</b>	14.3	80.8	78.5	17.6	66.6	66.4	<b>37.5</b>	<b>53.5</b>
Oracle	84.6	76.8	74.3	93.0	52.5	4.0	92.8	74.6	15.0	87.0	82.0	29.6	81.2	74.7	49.3	61.7

Methods		Clear Day (*)			* → Light Fog Day			* → Dense Fog Day			* → Snow Day			* → Clear Night		
		Car	Ped.	RV	Car	Ped.	RV	Car	Ped.	RV	Car	Ped.	RV	Car	Ped.	RV
<b>Unimodal without DA</b>	LiDAR Only	57.2	45.1	34.9	51.5	14.2	0.2	27.6	20.1	8.1	51.4	43.2	9.3	61.6	50.0	20.2
	RGB Only	79.8	<b>75.5</b>	67.7	82.2	39.2	0.2	70.9	53.3	<b>15.3</b>	75.5	77.3	19.5	46.9	52.6	16.0
	RGB Only, large	79.3	74.6	66.0	82.9	40.5	3.6	71.4	50.7	15.0	77.5	76.1	15.3	42.3	52.0	12.2
<b>Multimodal</b>	Entropy Fusion [16]	<b>81.8</b>	74.8	<b>69.8</b>	84	38.2	<b>5.8</b>	71.2	50	11.3	78	78.4	20.8	59.3	63.4	22.7
<b>Unimodal DA</b>	ADDA [22]	79.8	75.5	67.7	83.5	38.6	2.5	77.3	54.5	14.8	75.1	77.2	12.7	54.3	57.8	22.5
	RGB, CycleGAN [33]	79.8	75.5	67.7	85.5	35.2	3.7	80.2	61.3	14.2	75.6	79.1	21.5	64.0	65.6	28.3
	CyCADA [23]	79.8	75.5	67.7	82.8	33.5	1.3	78.6	55.2	15.1	74.6	77.5	19.3	63.9	66.1	29.2
<b>Multimodal DA</b>	Ours	<b>81.8</b>	74.8	<b>69.8</b>	<b>85.9</b>	<b>45.0</b>	4.6	<b>81.0</b>	<b>63.3</b>	14.3	<b>80.8</b>	<b>79.7</b>	<b>26.1</b>	<b>68.8</b>	<b>67.7</b>	<b>40.5</b>
<b>Oracle</b>	Entropy Fusion [16]	81.8	74.8	69.8	90.4	55.5	5	90.7	77.9	15	87.2	83.3	32.1	79.0	74.1	49.7

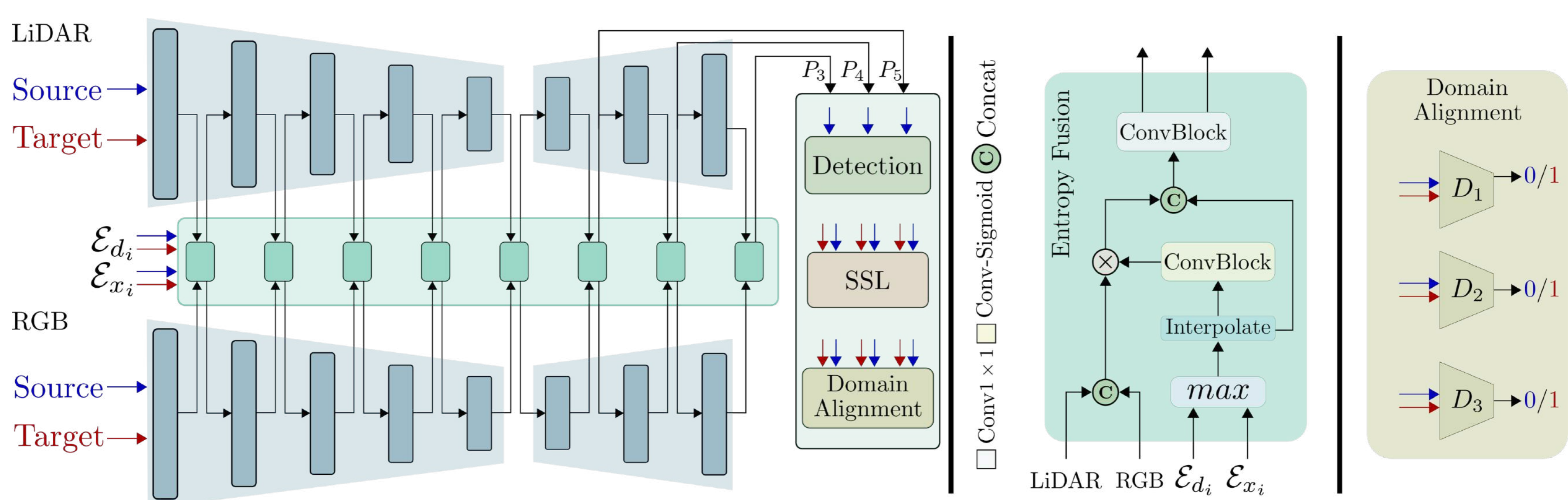


Figure 1: Architecture of the proposed model and domain adaptation approaches.

## Partners



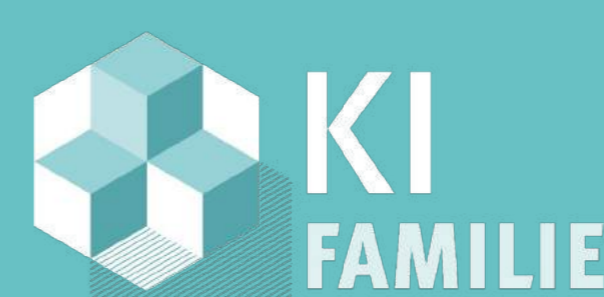
## External partners



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