

Deep Learning for Radar Data Exploitation in Autonomous Driving

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Motivations

Autonomous driving requires a high perception around the ego-vehicle for scene understanding.

Camera and lidar are commonly used to detect objects.

Automotive radar is the only one to be resiliant to adverse weather conditions.

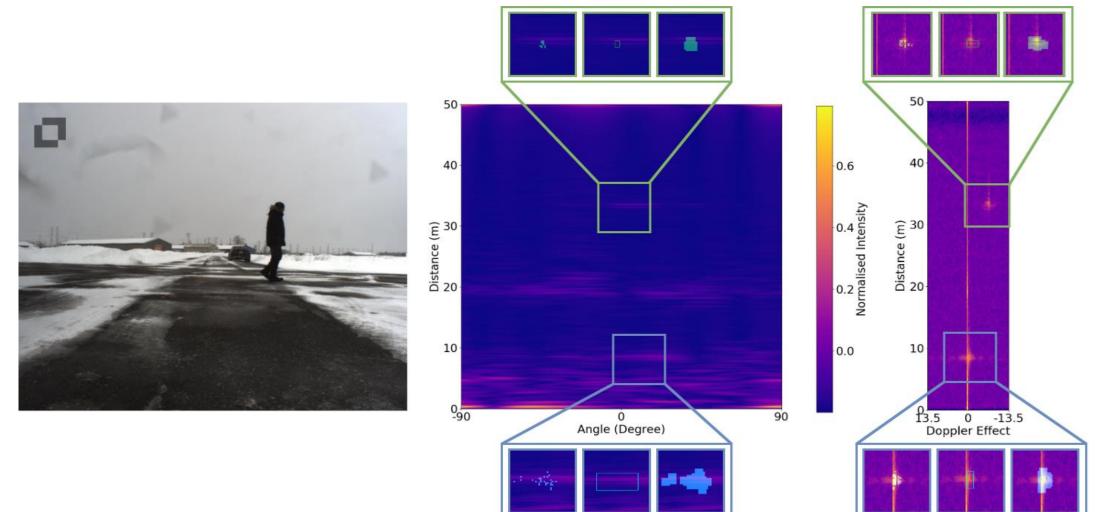
Problems

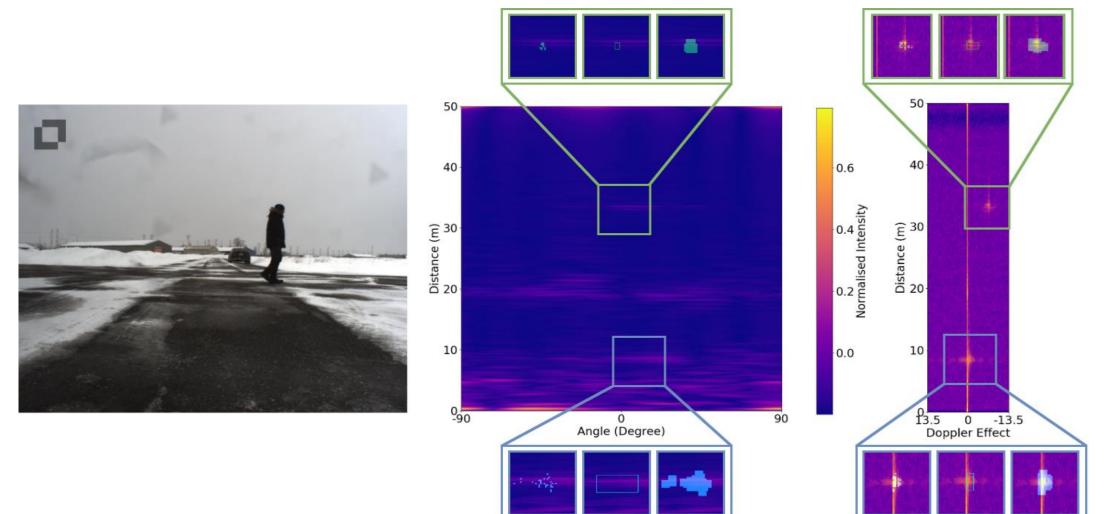
- How to find annotated raw radar data?
- How to create a suitable deep learning architecture for radar scene understanding?



CARRADA Dataset: Camera and Automotive Radar with Annotations [1]

Objective: create a dataset with a semi-automatic annotation tool to generate annotations in the raw radar data





Method:

- 1. Detect and track objects in the camera images.
- 2. Compute their physical properties.
- 3. Project them in a processed radar representation.
- 4. Cluster and track the objects in the processed radar sequence.
- 5. Project the clusters in the raw radar representation to obtain various annotations.
- Results: release of the first raw radar dataset with Range-Angle-Doppler annotations for scene understanding.

A scene from CARRADA dataset, with a pedestrian and a car. (left) Video frame provided by the frontal camera, showing a pedestrian at approximately 8m from the sensors and a car in the background at approximately 33m; (middle-right) Radar signal at the same instant in range-angle and range-Doppler representation respectively. Three types of annotations are provided: sparse points, bounding boxes and dense masks. The blue squares correspond to the pedestrian and the green ones to the car.

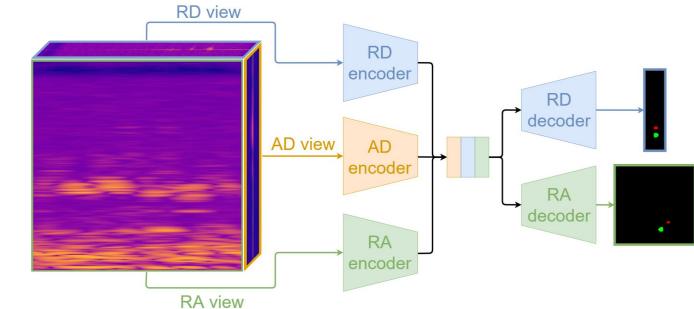
Radar Scene Understanding: Multi-View Radar Semantic Segmentation [2]

Objective: propose a deep learning architecture for scene understanding using raw radar data.

Contributions:

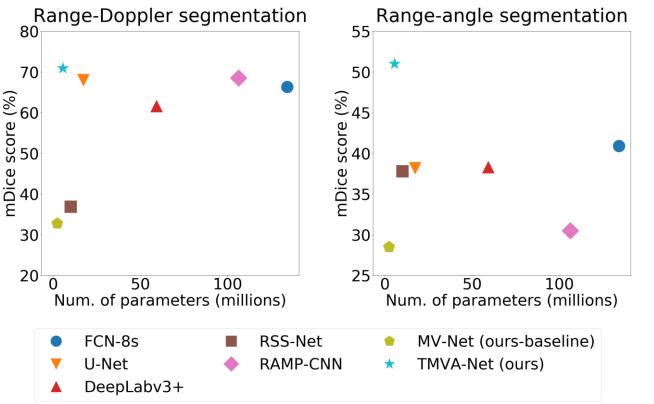
1. Architectures for multi-view radar semantic segmentation.

2. Combination of losses using a new coherence term.



Results of our method: 1. Outperforms adapted methods with significantly fewer parameters. 2. Provides **consistent** temporal and multi-view predictions based on qualitative results. 3. Generalizes well on

complex urban scenes.





Car Cyclist Pedestrian (d) (e) (a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Qualitative results on a test scene of CARRADA. (Top) camera image of the scene and results of the RD segmentation; (Bottom) Results of the RA Segmentation. (a) Radar view signal, (b) ground-truth mask, (c) FCN8s, (d) U-Net, (e) DeepLabv3+, (f) RSS-Net, (g) RAMP-CNN, (h) MV-Net (our baseline w/ wCE+SDice loss), (i) TMVA-Net (ours, w/ wCE+SDice loss), (j) TMVA-Net (ours, w/ wCE+SDice+CoL loss).

Create and release the first raw radar dataset with Range-Angle-Doppler annotations.

Propose a lightweight and efficient framework for multi-view radar semantic segmentation.

Conclusions and Perspectives

Improve the coherence loss and apply MVRSS framework to recent datasets

Explore multi sensor fusion in 3D point clouds for scene understanding.

[1] CARRADA Dataset: Camera and Automotive Radar with Range-Angle-Doppler Annotations, Arthur Ouaknine, Alasdair Newson, Julien Rebut, Florence Tupin, Patrick Pérez, ICPR 2020 [2] Multi-View Radar Semantic Segmentation, Arthur Ouaknine, Alasdair Newson, Patrick Pérez, Florence Tupin, Julien Rebut, Preprint, ArXiv 2021

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