

MOTIVATION & CONTRIBUTIONS

- Automotive radar: **robust to adverse weather conditions** while providing the **position and radial velocity** of surrounding objects.
- Contributions: **architectures** for multi-view radar semantic segmentation; a **combination of losses** adapted to objects' signatures with spatial coherence.

COMBINATION OF LOSSES

Let $f_{\theta}(\mathbf{x}) = \mathbf{p}$ be a segmentation model with parameters θ , input \mathbf{x} , output \mathbf{p} and \mathbf{y} the ground truth. Note $M \times N$ is the size of the view, such as $\Omega = [1, M] \times [1, N]$; and K the number of classes.

Weighted Cross Entropy

$$\mathcal{L}_{wCE}(\mathbf{y}, \mathbf{p}) = -\frac{1}{K} \sum_{k=1}^K w_k \sum_{(m,n) \in \Omega} \mathbf{y}[m, n, k] \log \mathbf{p}[m, n, k]$$

where $w_k \propto (\sum_y \sum_{(m,n) \in \Omega} \mathbf{y}[m, n, k])^{-1}$.

Soft Dice

$$\mathcal{L}_{SDice} = \frac{1}{K} \sum_{k=1}^K \left[1 - \frac{2 \sum_{(m,n)} \mathbf{y}[m, n, k] \mathbf{p}[m, n, k]}{\sum_{(m,n)} \mathbf{y}^2[m, n, k] + \mathbf{p}^2[m, n, k]} \right]$$

Coherence

$$\mathcal{L}_{CoL}(\mathbf{p}^{RD}, \mathbf{p}^{RA}) = \|\tilde{\mathbf{p}}^{RD} - \tilde{\mathbf{p}}^{RA}\|_F^2$$

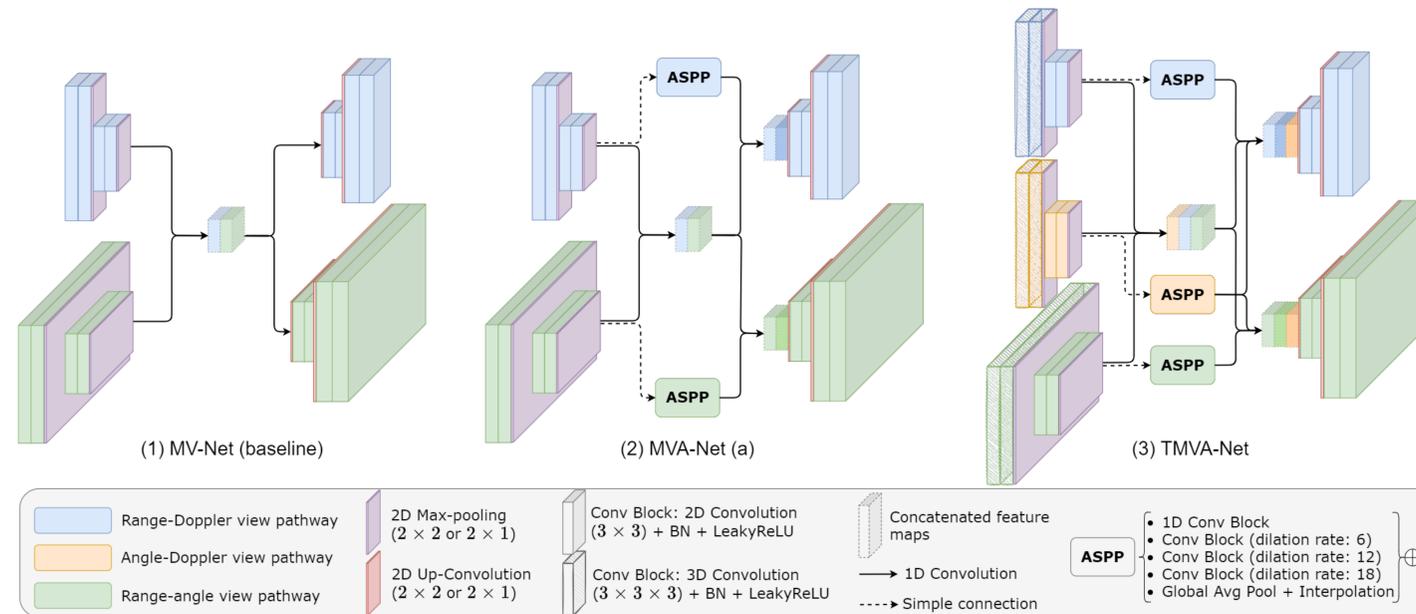
where $\|\cdot\|_F$ denotes the Frobenius norm; $\tilde{\mathbf{p}}^{RD}$, $\tilde{\mathbf{p}}^{RA}$ the highest probability maps of each range bin for each class.

Combination

$$\mathcal{L} = \lambda_{wCE}(\mathcal{L}_{wCE}^{RD} + \mathcal{L}_{wCE}^{RA}) + \lambda_{SDice}(\mathcal{L}_{SDice}^{RD} + \mathcal{L}_{SDice}^{RA}) + \lambda_{CoL} \mathcal{L}_{CoL}$$

where λ_{wCE} , λ_{SDice} and λ_{CoL} are weighting factors.

PROPOSED ARCHITECTURES



ABLATION STUDIES

Let RD and RA be the range-Doppler and range-angle views.

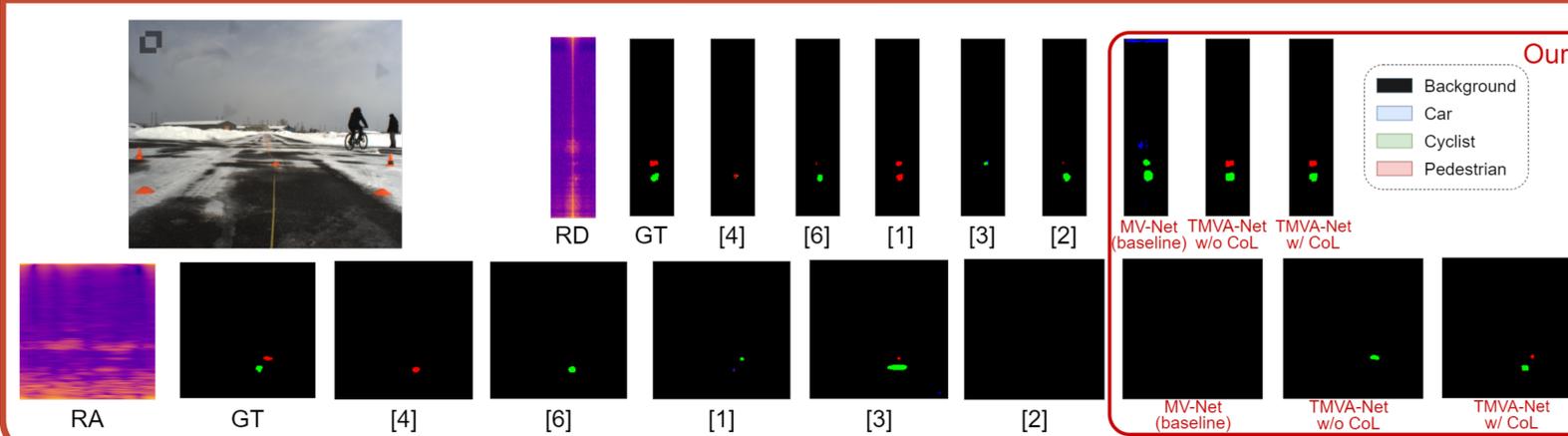
View	Method	#Param.↓	mIoU↑	mDice↑
RD	MV-Net (baseline)	2.4M	29.0	39.8
	MVA-Net (a)	3.6M	48.9	60.4
	MVA-Net (b)	4.8M	52.9	64.3
	TMVA-Net	5.6M	59.3	71.5
RA	MV-Net (baseline)	2.4M	26.8	28.5
	MVA-Net (a)	3.6M	28.1	31.1
	MVA-Net (b)	4.8M	36.7	43.9
	TMVA-Net	5.6M	40.1	49.3

Table 1: Performances of the proposed architectures.

Loss	RD view		RA view	
	mIoU	mDice	mIoU	mDice
CE	56.1	67.8	39.1	48.3
SDice	58.5	70.3	37.1	44.8
wCE	51.1	62.8	34.3	41.1
CE+SDice	45.2	54.0	38.8	46.9
wCE+SDice	59.3	71.5	40.1	49.3
wCE+SDice+CoL	<u>58.7</u>	<u>70.9</u>	41.3	51.0

Table 2: Performances of various loss combinations.

QUALITATIVE RESULTS ON THE CARRADA-TEST DATASET [5]



REFERENCES

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- X. Gao, G. Xing, S. Roy, and H. Liu. RAMP-CNN: A Novel Neural Network for Enhanced Automotive Radar Object Recognition. In *Sensor Journal*, 2020.
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- O. Ronneberger, P. Fischer, and T. Brox. U-Net: Convolutional Networks for Biomedical Image Segmentation. In *MICCAI*, 2015.

Github: <https://github.com/valeoai/MVRSS>

Website: <https://arthouaknine.github.io/codeanddata/mvrss>

QUANTITATIVE RESULTS

View	Method	#Param.(M) ↓	mIoU ↑	mDice ↑
RD	FCN-8s [4]	134.3	54.7	66.3
	U-Net [6]	17.3	55.4	68.0
	DeepLabv3+ [1]	59.3	50.8	61.6
	RSS-Net [3]	10.1	32.1	36.9
	RAMP-CNN [2]	106.4	<u>56.6</u>	<u>68.5</u>
	MV-Net (ours-base.)	2.4*	29.0	32.8
	TMVA-Net (ours)	<u>5.6*</u>	58.7	70.9
RA	FCN-8s [4]	134.3	<u>34.5</u>	<u>40.9</u>
	U-Net [6]	17.3	32.8	38.2
	DeepLabv3+ [1]	59.3	32.7	38.3
	RSS-Net [3]	10.1	32.1	37.8
	RAMP-CNN [2]	106.4	27.9	30.5
	MV-Net (ours-base.)	2.4*	26.8	28.5
	TMVA-Net (ours)	<u>5.6*</u>	41.3	51.0

Table 3: Performances on the CARRADA-Test dataset [5] for RD and RA views, (“*”) corresponds to a single model that segments both views.