

OVeNet: Offset Vector Network for Semantic Segmentation

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Abstract

Semantic segmentation is a fundamental task in visual scene understanding. We focus on the supervised setting, where ground-truth semantic annotations are available. Based on knowledge about the high regularity of real-world scenes, we propose a method for improving class predictions by learning to selectively exploit information from neighboring pixels. In particular, our method is based on the prior that for each pixel, there is a seed pixel in its close neighborhood sharing the same prediction with the former. Motivated by this prior, we design a novel two-head network, named Offset Vector Network (OVeNet), which generates both standard semantic predictions and a dense 2D offset vector field indicating the offset from each pixel to the respective seed pixel, which is used to compute an alternative, seed-based semantic prediction. The two predictions are adaptively fused at each pixel using a learnt dense confidence map for the predicted offset vector field. We supervise offset vectors indirectly via optimizing the seed-based prediction and via a novel loss on the confidence map. Compared to the baseline state-of-the-art architectures HRNet and HRNet+OCR on which OVeNet is built, the latter achieves significant performance gains on two prominent benchmarks for semantic segmentation of driving scenes, namely Cityscapes and ACDC. Code is available at <https://github.com/stamatisalex/OVeNet>.

1. Introduction

Semantic segmentation is one of the most central tasks in computer vision. In particular, it is the task of assigning a class to every pixel in a given image. It has lots of applications in a variety of fields, such as autonomous driving [7, 32], robotics [3, 71], and medical image processing [1, 64], where pixel-level labeling is critical.

The adoption of convolutional neural networks (CNNs) [54] for semantic image segmentation has led to a tremendous improvement in performance on challenging, large-

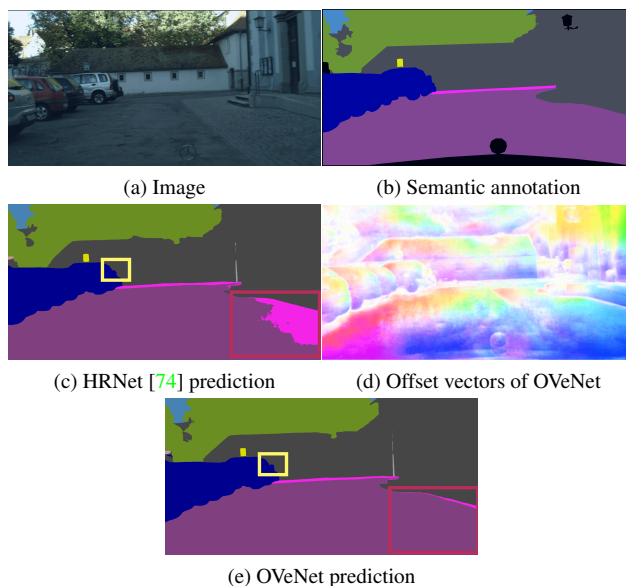


Figure 1. Real-world scenes have a high degree of regularity. We propose a semantic segmentation method which can exploit this regularity, by learning to selectively leverage information from neighboring *seed* pixels. Our proposed Offset Vector Network (OVeNet) can improve upon state-of-the-art architectures [74] by estimating the offset vectors to such seed pixels and using them to refine semantic predictions.

scale datasets, such as Cityscapes[19], MS COCO [49] and ACDC [65]. Most of the related works [12, 15, 58, 74, 85] focus primarily on architectural modifications of the employed networks in order to better combine global context aggregation and local detail preservation, and use a simple loss that is computed on individual pixels. The design of more sophisticated losses [35, 56, 86] that take into account the structure which is present in semantic labelings has received significantly less attention. Many supervised techniques utilize a pixel-level loss function that handles predictions for individual pixels independently of each other. By doing so, they ignore the high regularity of real-world scenes, which can eventually profit the final model's per-

formance by leveraging information from adjacent pixels. Thus, these methods misclassify several pixels, primarily near semantic boundaries, which leads to major losses in performance.

Based on knowledge about the high regularity of real scenes, we propose a method for improving class predictions by learning to selectively exploit information from neighboring pixels. In particular, the general nature of this idea is applicable on SOTA models like HRNet [74] or HRNet + OCR [86] and can extend these models by adding a second head to them capable of achieving this goal.

The architecture of our Offset Vector Network (OVeNet) is shown in Fig. 2. In particular, following the base architecture of the backbone model (e.g HRNet or HRNet + OCR), the first head of our network outputs the initial pixel-level semantic predictions. In general, two pixels \mathbf{p} and \mathbf{q} that belong to the same category share the same semantic outcome. If the pixels belong to the same class, using the label of \mathbf{q} for estimating class at the position of \mathbf{p} results in a correct prediction.

We leverage this property by learning to identify *seed pixels* which belong to the same class as the examined pixel, whenever such pixels exist, in order to selectively use the prediction at the former for improving the prediction at the latter. This idea is motivated by a prior which states for every pixel \mathbf{p} associated with a 2D semantically segmented image, there exists a seed pixel \mathbf{q} in the neighborhood of \mathbf{p} which shares the same prediction with the former. In order to predict classes with this scheme, we need to find the regions where the prior is valid. Furthermore, in order to point out the seed pixels in these regions, we must predict the offset vector $\mathbf{o}(\mathbf{p}) = \mathbf{q} - \mathbf{p}$ for each pixel \mathbf{p} .

As a result, we design a second head that generates a dense offset vector field and a confidence map. The predicted offsets are used to resample the class predictions from the first head and generate a second class prediction. The outcomes from the two heads are fused adaptively using the learnt confidence map as fusion weights, in order to down-weight the offset-based prediction and rely primarily on the basic class prediction in regions where the prior is not valid. Thanks to using seed pixels for prediction, our network classifies several pixels with incorrect initial predictions, e.g., boundary pixels, to the correct classes. Thus, it improves the shape as well as the form of the corresponding segments, leading to more realistic results. Last but not least, we propose a confidence loss which supervises the confidence map explicitly and further improves performance. An illustrative example of this concept is depicted in Fig. 1, where OVeNet outperforms the baseline HRNet [74] model, since it enlarges correctly the road and the car segment (red and yellow frame correspondingly) and reduces the total number of misclassified pixels.

We evaluate our method extensively on 2 primary

benchmarks for semantic segmentation of driving scenes: Cityscapes [19] and ACDC [65]. We implement our offset vector branch both on HRNet [74] and HRNet+OCR [87]. Our approach significantly improves the initial models' output predictions by achieving better mean and per-class results. We conduct a thorough qualitative and quantitative experimental comparison to show the clear advantages of our method over previous SOTA techniques.

2. Related Work

Semantic segmentation architectures. Fully convolutional networks [66, 67] were the first models that re-architected and fine-tuned classification networks to direct dense prediction of semantic segmentation. They generated low-resolution representations by eliminating the fully-connected layers from a classification network (e.g AlexNet [38], VGGNet [68] or GoogleNet [69]) and then estimating coarse segmentation maps from those representations. To create medium-resolution representations [11, 12, 13, 42, 85], fully convolutional networks were expanded using dilated/atrous convolutions, which replaced a few strided convolutions and their associated ones. Following, in order to restore high-resolution representations from low-resolution representations an upsample process was used. This process involved a subnetwork that was symmetric to the downsample process (e.g VGGNet [68]), and included skipping connections between mirrored layers to transform the pooling indices (e.g. DeconvNet [58]). Other methods include duplicating feature maps, which is used in architectures like U-Net [64] and Hourglass [6, 18, 20, 33, 57, 70, 80, 82] or encoder-decoder architectures [2, 61]. Lastly, the process of asymmetric upsampling [5, 16, 30, 48, 60, 72, 78, 91] has also been extensively researched.

The models' representations were then enhanced to include multi-scale contextual information [8, 9, 92]. PSPNet [93] utilized regular convolutions on pyramid pooling representations to capture context at multiple scales, while the DeepLab series [12, 13] used parallel dilated convolutions with different dilation rates to capture context from different scales. Recent research [27, 40, 81] proposed extensions, such as DenseASPP [81], which increased the density of dilated rates to cover larger scale ranges. Other studies [15, 25, 44] used encoder-decoder structures to exploit the multi-resolution features as the multi-scale context. Here belongs the HRNet [74], the baseline model of our method. HRNet connects high-to-low convolution streams in parallel. It ensures that high-resolution representations are maintained throughout the entire process and creates dependable high-resolution representations with accurate positional information by repeatedly merging the representations from various resolution streams. Applying additionally the OCR [86] method, HRNet + OCR is one of the leading models in the task of semantic segmentation.

Lately, transformers have been successful in computer vision tasks demonstrating their effectiveness. ViT [22] was the first attempt to use the vanilla transformer architecture [73] for image classification without extensive modification. Unlike later methods, such as PVT [76] and Swin [53], that incorporated vision-specific inductive biases into their architectures, the plain ViT suffers inferior performance on dense predictions due to weak prior assumptions. To tackle this problem, the ViT-Adapter [17] was introduced, which allowed plain ViT to achieve comparable performance to vision-specific transformers and achieves the SOTA performance on this task.

Semantic segmentation loss functions. Image segmentation has highly correlated outputs among the pixels. Converting pixel labeling problem into an independent problem can lead to problems such as producing results that are spatially inconsistent and have unwanted artifacts, making pixel-level classification unnecessarily challenging. To solve this problem, several techniques [14, 37, 52, 95] have been developed, such as integrating structural information into segmentation. For instance, Chen et al. [12] utilized denseCRF [37] for refining the final segmentation result. Following, Zheng et al. [95] and Liu et al. [52] made the CRF module differentiable within the deep neural network. Other methods that have been used to encode structures include pairwise low-level image cues like grouping affinity [51, 55] and contour cues [4, 10]. GANs [63] are another alternative for imposing structural regularity in the neural network output. However, these methods may not work well in cases where there are changes in visual appearance or may require expensive iterative inference procedures. Thus, Ke et al. [35] introduced AAFs, which are easier to train than GANs and more efficient than CRF without run-time inference. There has been also proposed another loss function [56] suitable for in real time applications that pulls the spatial embeddings of pixels belonging to the same instance together.

Offset Vector-Based methods are essential for image analysis tasks that involve adjacent pixels. In particular, they can effectively exploit the information contained in neighbouring pixels, handle image distortions and noise, and improve the accuracy of various image analysis tasks. They can be used in applications such as depth estimation [59] or semantic segmentation [56, 88]. Based on knowledge about the high regularity of real 3D scenes, P3Depth [59] is a method used for 3D depth estimation learns to selectively leverage information from coplanar pixels to improve the predicted depth. In semantic segmentation, SegFix [88] is a model-agnostic post-processing scheme that improved the boundary quality for the segmentation result. Motivated by the empirical observation that the label predictions of interior pixels are more reliable, SegFix replaced the originally unreliable predictions of boundary pixels by the predictions

of interior pixels. OVeNet provides another perspective to use offset vectors and structure modeling by matching the relations between neighbouring pixels in the label space. Although our approach is inspired by the P3Depth idea, we focus on a different task in the 2D world which is semantic segmentation. Moreover, the key difference between our method and SegFix is the timing of when they are applied. Essentially, OVeNet integrates the offset vector learning process into the model training, while SegFix applies the offset correction as a separate post-processing step.

3. Method

In this section, we will analyze our method shown in Fig. 2. Firstly, in Sec. 3.1 we give some basic notation and terminology of semantic segmentation. As we mentioned before in Sec. 1, our network estimates semantic labels by selectively combining information from each pixel and its corresponding seed pixel. The intuition and the advantages of using seed pixels to improve the initial prediction of a model are described analytically in Sec. 3.2. Lastly, in Sec. 3.3 we introduce an additional confidence loss, which further enhances our method.

3.1. Terminology

Semantic segmentation requires learning a dense mapping $f_\theta : I(u, v) \rightarrow S(u, v)$ where I is the input image with spatial dimensions $H \times W$, S is the corresponding output prediction map of the same resolution, (u, v) are pixel coordinates in the image space and θ are the parameters of the mapping f . In supervised semantic segmentation, a ground-truth semantically segmented map H is available for each image during training. The aim is to optimize the function parameters θ such that the predicted output map is as close as possible to the ground-truth map across the entire training set T . This can be achieved by minimizing the difference between the predicted and ground-truth images:

$$\min_{\theta} \sum_{(I, H) \in T} \mathcal{L}(f_\theta(I), H) \quad (1)$$

where \mathcal{L} is a loss function that penalizes variations between the prediction and the ground truth.

3.2. Seed Pixel Identification

Let us assume we have one pixel \mathbf{p} which belongs to segment of a semantically segmented image. By definition, every other pixel on this segment has the same class value. Thus, ideally, in order to get all of the class values accurate, the network only has to predict the class at one of these pixels, \mathbf{q} . This pixel can be interpreted as the seed pixel that describes the segment-class. Finally, we let the network find this seed pixel and the corresponding region.

Let us define a prior which is a relaxed version of the previous idea.

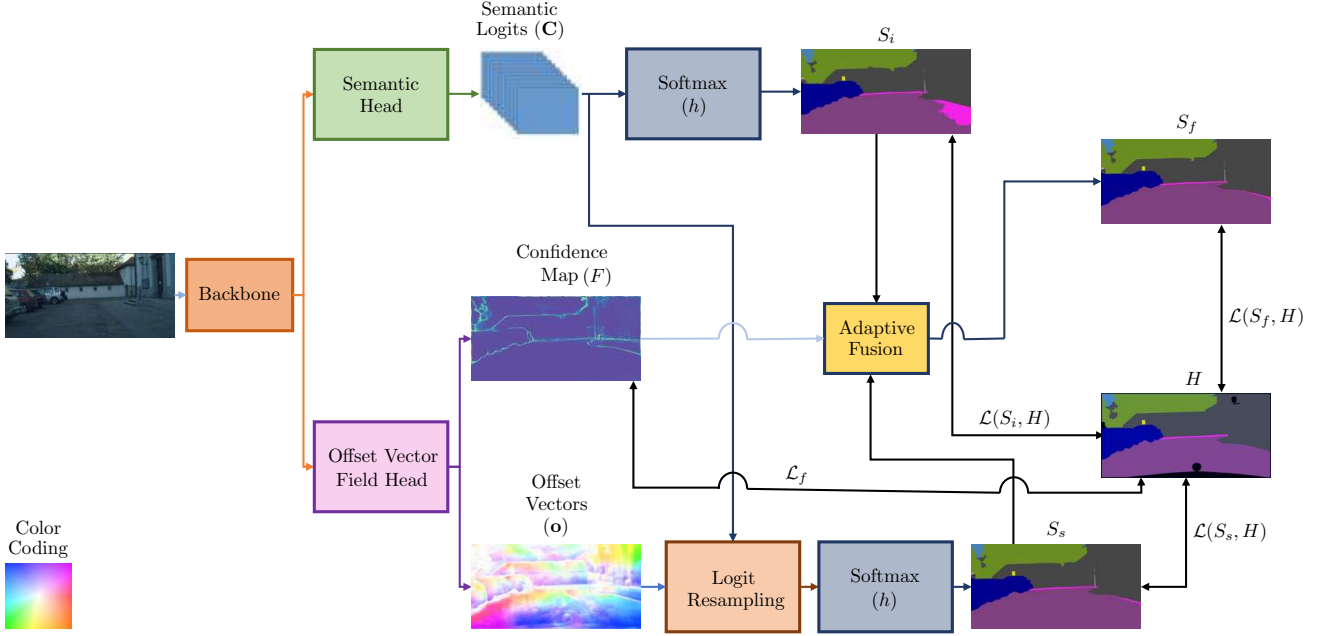


Figure 2. **Overview of OVeNet.** OVeNet is a two-headed network. The first head outputs semantic logits (\mathbf{C}), while the second head outputs a dense offset vector field (\mathbf{o}) identifying positions of seed pixels along with a confidence map (F). The logits are passed through a softmax function and output the initial class prediction (S_i) of the model. Then, the offset vectors are used to resample the logits from the first head and generate a second class prediction (S_s). The two predictions are adaptively fused using the confidence map resulting in the final prediction S_f . For the visualization of the offset vectors we use the optical flow color coding from [29]. Smaller vectors are lighter and color represents the direction.

Definition 1 For every pixel \mathbf{p} associated with a 2D semantically segmented image, there exists a seed pixel \mathbf{q} in the neighborhood of \mathbf{p} which shares the same prediction with the former.

In general, there may be numerous seed pixels for \mathbf{p} or none at all. Given that the Definition 1 holds, semantic segmentation task for \mathbf{p} can be solved by identifying \mathbf{q} . For this reason, we let our network predict the offset vector $\mathbf{o}(\mathbf{p}) = \mathbf{q} - \mathbf{p}$. Thus, we design our model so that it features a second, offset head and let this offset head predict a dense offset vector field $\mathbf{o}(u, v)$. The two heads of the network share a common main body and then they follow different paths. We resample the initial logits \mathbf{C} , being predicted by the first head, using the estimated offset vector field via:

$$\mathbf{C}_s(\mathbf{p}) = \mathbf{C}(\mathbf{p} + \mathbf{o}(\mathbf{p})) \quad (2)$$

To manage fractional offsets, bilinear interpolation is used. The resampled logits are then used to compute a second semantic segmentation prediction:

$$\begin{aligned} S_s(u, v) &= h(\mathbf{C}_s(u, v), u, v) \\ \Rightarrow S_s(\mathbf{p}) &= S_i(\mathbf{p} + \mathbf{o}(\mathbf{p})) \end{aligned} \quad (3)$$

based on the seed locations. In our experiment, $h = \text{softmax}$.

Due to the fact that the prior is not always correct, the initial semantic prediction S_i may be preferred to the seed-based prediction S_s . To account for such cases, the second head additionally predicts a confidence map $F(u, v) \in [0, 1]$, which represents the model’s confidence in adopting the predicted seed pixels for semantic segmentation via S_s . By adaptively fusing S_i and S_s , the confidence map is used to compute the final prediction:

$$S_f(\mathbf{p}) = (1 - F(\mathbf{p}))S_i(\mathbf{p}) + F(\mathbf{p})S_s(\mathbf{p}) \quad (4)$$

We apply supervision to each of S_f , S_s , and S_i in our model, by optimizing the following loss:

$$\mathcal{L}_{\text{semantic}} = \mathcal{L}(S_f, H) + \kappa \mathcal{L}(S_s, H) + \lambda \mathcal{L}(S_i, H) \quad (5)$$

with κ and λ being hyperparameters and H denotes the GT train ids of each class for each pixel. In this way, we encourage the initial model’s head to output an accurate representation across all pixels, even when they have a high confidence value, and the offset vector head to learn high confidence values for pixels for which the definition 1 holds and low confidence values for pixels for which the prior does not.

This formulation, however, comes with a drawback. The model is not supervised directly on the offsets. In fact, it could just predict zero offsets everywhere and yet give

valid S_s and S_f predictions that are equal to S_i . Since the initial predictions S_i are erroneously smoothed around semantic boundaries due to the regularity of the mapping f_θ in the case of neural networks, this undesirable behavior is avoided in practice. As a result, predicting a non-zero offset that points away from the boundary provides a lower value for $\mathcal{L}_{\text{semantic}}$ for pixels on either side of the boundary. This happens due to the fact that such an offset utilizes a seed pixel for S_s that is further away from the border and suffers from reduced inaccuracy due to smoothing. These non-zero offsets are also transmitted from the boundaries to the inner sections of areas with smooth segments, helping the network in predicting non-trivial offsets due to the regularity of the mapping that forms the offset vector field.

3.3. Confidence-Based Loss

Our confidence loss is based on the concept that given a pixel coordinate, its surrounding pixels should be in the same segment. For each pixel \mathbf{p} , we define the confidence loss as follows:

$$\begin{aligned} \mathcal{L}_f(\mathbf{p}) = & -\mathbb{1}_{H(\mathbf{p})=H(\mathbf{p}+\mathbf{o}(\mathbf{p}))} \log F(\mathbf{p}) \\ & -\mathbb{1}_{H(\mathbf{p}) \neq H(\mathbf{p}+\mathbf{o}(\mathbf{p}))} \log(1 - F(\mathbf{p})) \end{aligned} \quad (6)$$

This idea is motivated by the fact that confidence should have large value, for those pixels whose offset vector points to seed pixels with the same class. Similarly, confidence should have small value, for those pixels whose offset vector points to seed pixels with different class.

To sum up, the complete loss is:

$$\mathcal{L}_{\text{final}} = \mathcal{L}_{\text{semantic}} + \mathcal{L}_f \quad (7)$$

4. Experiments

To evaluate the proposed method, we carry out comprehensive experiments on Cityscapes and ACDC dataset. Experimental results demonstrate that our method achieved the highest performance, outperforming all other baselines. Following, we first introduce the datasets, evaluation metrics and implementation details in Sec. 4.1. We then compare our method to SOTA approaches in Sec. 4.2. Finally, we perform a series of ablation experiments on Cityscapes dataset in Sec. 4.3.

4.1. Experimental Setup

In this section, we present Cityscapes and ACDC datasets, which are used to evaluate our approach. Evaluation on these datasets is performed using standard semantic segmentation metrics explained below.

Cityscapes [19] is a challenging dataset, tasked for urban scene understanding. It includes semantic, instance-wise, and dense pixel annotations for 30 classes divided into eight

groups (flat surfaces, humans, vehicles, constructions, objects, nature, sky, and void). From these 30 classes only 19 classes are used for parsing evaluation. Around 5000 high quality pixel-level finely annotated images and 20000 coarsely annotated images make up the collection. During multiple months, daytimes, and ideal weather circumstances, data was collected in 50 cities. The finely annotated 5000 images are divided into 2.975, 500, 1.525 images for training, validation and testing respectively.

ACDC [65] is a demanding dataset, used for training and testing semantic segmentation methods on adverse visual conditions. It consists of a big collection of 4006 images divided evenly between four frequent unfavorable conditions: fog, dark, rain, and snow. It consists of 19 semantic classes, coinciding exactly with the evaluation classes of the Cityscapes dataset. ACDC is manually split into four sets corresponding to the examined conditions: 1000 foggy, 1006 nighttime, 1000 rainy and 1000 snowy images. Each set of each adverse condition is split into 400 training, 100 validation and 500 test images, except the nighttime set with 106 validation images. This results in a total of 1600 training and 406 validation images with public annotations and 2000 test images with annotations withheld for benchmarking purposes.

Evaluation Metrics. The mean of class-wise intersection over union (mIoU) is adopted as the evaluation metric. In addition to the mean of class-wise intersection over union (mIoU), we report other three scores on the test set: IoU category (cat.), iIoU class (cla.) and iIoU category (cat.)

Implementation Details. Our network consists of two heads. The first head outputs 19 channels, one for each class. The second head outputs three channels: one for each coordinate of the offset vectors and one for confidence. These two heads follow the structure of HRNet. Both OVeNet and the baseline HRNet are initialized with pre-trained ImageNet [38] weights. This initialization is important to achieve competitive results as in [74]. Following the same training protocol as in [74], the data are augmented by random cropping (from 1024×2048 to 512×1024 in Cityscapes and from 1080×1920 to 540×960 in ACDC), random scaling in the range of $[0.5, 2]$, and random horizontal flipping. We use the SGD optimizer with the base learning rate of 0.01, the momentum of 0.9 and the weight decay of 0.0005. The number of epochs used for training is 484. For lowering the learning rate, a poly learning rate policy with a power of 0.9 is applied. The offset vectors are restricted via a tanh layer to have a maximum length of τ in normalized image coordinates. After an ablation study shown in Sec. 4.3, we set τ to 0.5 by default and the branch will occur on the last (4^{th}) stage of HRNet. The confidence map is predicted through a sigmoid layer. For S_i , S_s and S_f predictions, Ohem Cross Entropy Loss is used. It is remarkable that, at first, the model computed the S_i , S_s , S_f

predictions directly but that led to low mIoU results. On the other hand, the final model with the best results outputted the S_i , S_s , S_f logits. The loss weights λ and μ are set to 0.5. In addition, the confidence based loss is applied using the final semantic prediction S_f .

4.2. Comparison with the State of the Art

Cityscapes. The results on Cityscapes which is the major database focusing on semantic understanding of urban street scenes are shown below. We achieve better results on Cityscapes than both the initial HRNet and HRNet + OCR model under similar training time, outperforming prior SOTA methods. Table 1 compares our method with SOTA methods on the Cityscapes test set. All the results are with six scales and flipping. Two cases w/o using coarse data are evaluated: One is about the model learned on the train set, and the other is about the model learned on the train + val set. In both cases our offset vector - based model achieves the superior performance. To become more specific, we achieve a superior relative performance gain of 1.4% in mIoU, 2.4% in iIoU cla., 0.4% in IoU cat. and 1.4% in iIoU cat when the model is learned only on train set and a gain of 0.5% in mIoU when the model is learned on both train + val set. We can also observe that OVeNet built on HRNet and learned only on the training set, outperforms initial HRNet’s mIoU learned only on training set as well as both the training and validation sets. Table 2 analytically compares our approach with HRNet’s per class results. As we can see our method achieves better results in the majority of classes. Our offset vector-based model learns an implicit representation of different objects which can benefit the overall semantic segmentation estimation capability of the network. Regarding val set results, HRNet achieves 81.8% mIoU while OVeNet built on it surpasses it reaching 82.4% mIoU.

Qualitative results on Cityscapes support the above findings, as shown in Fig. 3. To be more specific, from left to right, we depict the RGB input image, GT image, CCNet’s [28], DANet’s [24], HRNet’s [87] and our model’s prediction. Specifically, our model demonstrates successful classification of false predicted pixels (identified by a red frame) in the first row of the image. Furthermore, the model accurately eliminates the terrain segment that had been previously incorrectly classified in the image (blue frame). In the second row, OVeNet exhibits superior performance compared to previous models, as it accurately expands the sidewalk and the pole depicted in the blue and yellow frames, respectively. Furthermore, not only it successfully eliminates discontinuities in the pink frame, but also results in a better representation of the bicycle’s shape. As far as the third set of images is concerned, our model reduces the false prediction made by HRNet in the sidewalk segment achieving a better final result. Last but not least,

Table 1. **Semantic segmentation results on Cityscapes test set.**

We compare our method against SOTA methods as in [74]. D-ResNet-101 = Dilated-ResNet-101. By default, OVeNet is built on HRNet, unless stated otherwise.

	backbone	mIoU	iIoU cla.	IoU cat.	iIoU cat.
<i>Model learned on the train set</i>					
PSPNet [92]	D-ResNet-101	78.4	56.7	90.6	78.6
PSANet [94]	D-ResNet-101	78.6	-	-	-
PAN [39]	D-ResNet-101	78.6	-	-	-
AAF [34]	D-ResNet-101	79.1	-	-	-
HRNet [74]	HRNetV2-W48	80.4	59.2	91.5	80.8
OVeNet	HRNetV2-W48	81.8	61.6	91.9	82.2
<i>Model learned on the train+val set</i>					
GridNet [23]	-	69.5	44.1	87.9	71.1
LRR-4x [26]	-	69.7	48.0	88.2	74.7
DeepLab [8]	D-ResNet-101	70.4	42.6	86.4	67.7
LC [41]	-	71.1	-	-	-
Piecewise [47]	VGG-16	71.6	51.7	87.3	74.1
FRN [62]	-	71.8	45.5	88.9	75.1
RefineNet [46]	ResNet-101	73.6	47.2	87.9	70.6
PEARL [31]	D-ResNet-101	75.4	51.6	89.2	75.1
DSSPN [43]	D-ResNet-101	76.6	56.2	89.6	77.8
LKM [60]	ResNet-152	76.9	-	-	-
DUC-HDC [75]	-	77.6	53.6	90.1	75.2
SAC [90]	D-ResNet-101	78.1	-	-	-
DepthSeg [36]	D-ResNet-101	78.2	-	-	-
ResNet38 [77]	WResNet-38	78.4	59.1	90.9	78.1
BiSeNet [83]	ResNet-101	78.9	-	-	-
DFN [84]	ResNet-101	79.3	-	-	-
PSANet [94]	D-ResNet-101	80.1	-	-	-
PADNet [79]	D-ResNet-101	80.3	58.8	90.8	78.5
CFNet [89]	D-ResNet-101	79.6	-	-	-
Auto-DeepLab [50]	-	80.4	-	-	-
DenseASPP [92]	WDenseNet-161	80.6	59.1	90.9	78.1
SVCNet [21]	ResNet-101	81.0	-	-	-
ANN [96]	D-ResNet-101	81.3	-	-	-
CCNet [28]	D-ResNet-101	81.4	-	-	-
DANet [24]	D-ResNet-101	81.5	-	-	-
HRNet [74]	HRNetV2-W48	81.6	61.8	92.1	82.2
HRNet + OCR [87]	HRNetV2-W48	81.9	62.0	92.0	82.5
OVeNet (HRNet + OCR)	HRNetV2-W48	82.4	61.6	91.9	82.2

in the last set of images, our model effectively reduces the pole (pink frame) in the segmentation output. Despite the presence of some errors that were not present in the initial HRNet, our model significantly increases the number of pixels that correctly belong to the ‘bus’ category, resulting in a superior prediction compared to the baseline. To sum up, OVeNet surpasses the HRNet’s performance.

ACDC. The results on ACDC, which targets semantic understanding of driving scenes in adverse visual conditions, are shown below. We also achieve far better results than the initial HRNet under similar training time, outperforming prior SOTA methods. Table 4 compares our approach with SOTA models not only on all methods but also on different conditions of the ACDC test set. OVeNet improves the initial HRNet model by 2.5% mIoU in ‘All’ conditions. Additionally, we can observe from the per class results shown on Table 3 on different conditions, that our approach outperforms the HRNet’s one in the vast majority of classes as well as in the total mIoU score. Specifically, on foggy days, performance on classes containing small-instance instances, such person, rider, and bicycle, is very low. This is likely because of the combined effect of contrast reduction

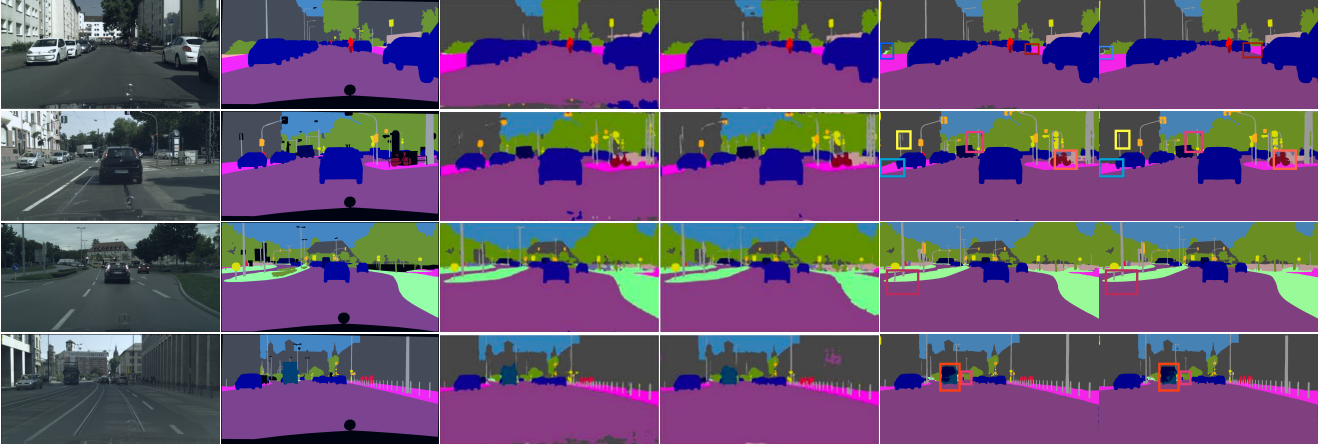


Figure 3. **Qualitative results of selected examples on Cityscapes.** From left to right: RGB Input Image, GT, CCNet [28], DANet [24], HRNet [74], OVeNet. Best viewed on a screen and zoomed in.

Table 2. **Per Class Results on Cityscapes test set**

Method	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motore.	bicycle	mIoU
HRNet [74]	98.73	87.49	93.65	56.48	61.57	71.57	78.76	81.81	93.99	74.11	95.68	87.95	73.72	96.35	69.94	82.52	76.93	70.88	78.02	80.40
OVeNet	98.74	87.41	93.79	61.65	64.00	71.35	78.98	81.65	94.00	73.42	95.81	87.99	74.36	96.42	74.76	87.70	82.83	71.77	77.86	81.82
HRNet + OCR	98.77	87.85	93.72	57.75	63.92	71.74	78.56	81.77	94.06	73.69	95.68	88.04	74.64	96.46	76.40	88.78	84.63	71.79	78.63	81.90
OVeNet (HRNet + OCR)	98.79	87.47	93.86	62.97	64.41	70.80	78.45	81.13	93.99	73.31	95.72	88.08	74.90	96.47	76.95	89.95	88.48	71.87	78.43	82.42

and poor resolution for examples of these classes that are far from the camera. There is also a huge performance boost of approximately 10% and 15% on the "bus" and "truck" class respectively. Moreover, it is more difficult to separate classes at night that are often dark or poorly lit, such as buildings, vegetation, traffic signs, and the sky. This behaviour is observed also in offset vector performance as they have small values when the visibility is limited. Lastly, during night and snow conditions, road and sidewalk performance is at its lowest, which can be attributed to misunderstanding between the two classes as a result of their similar look. As for val set results, HRNet achieves 75.5% mIoU while our OVeNet surpasses it reaching 75.9% mIoU.

Qualitative results on ACDC support the above findings, as shown in Fig. 4. To be more specific, from up to down, we depict the input RGB image, the GT, the initial HRNet's output and our model's output. In the first column, we can underline that our model tries to enlarge correctly the sidewalk segments in both red and green frames and reduces the erroneously terrain segment predicted by the initial model. As far as the second set of images is concerned, HRNet classifies incorrectly the sign of the house into the traffic sign class (red frame). On the contrary, our model corrects not only this mistake, but also a discontinuity occurred in the yellow frame. Last but not least, regarding the last set of materials, our offset vector - based model eliminates correctly the sidewalk area (red framework), as in the initial

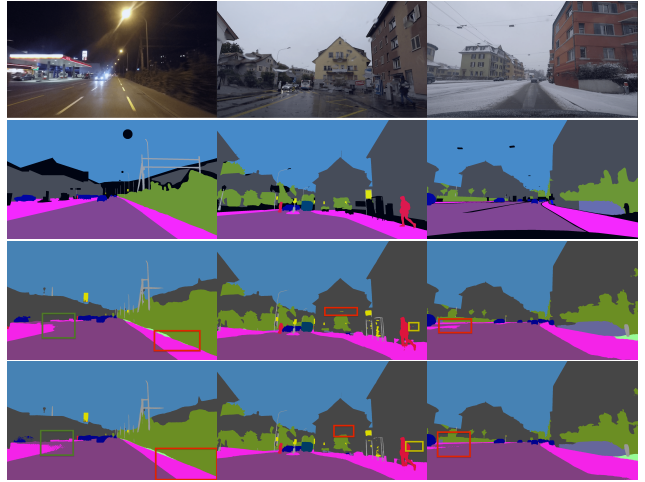


Figure 4. **Qualitative results of selected examples on ACDC.** Up to down: RGB, GT, HRNet [74], OVeNet. Best viewed on a screen and zoomed in.

image there is no such area. To sum up, OVeNet surpasses HRNet's performance.

4.3. Ablation study

In order to experimentally confirm our design choices for the offset vector - based model, we performed an ablation study, as shown in Table 5. We trained and evalu-

Table 3. **Per Class Results on ACDC test set.** OVeNet is built on HRNet.

Condition	Method	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mIoU
Fog	HRNet	95.3	81.1	89.7	54.2	48.1	60.3	76.2	76.0	89.1	78.1	98.3	58.8	60.1	83.3	50.5	47.9	86.4	49.8	36.3	69.3
	OVeNet	95.7	82.1	90.6	55.5	50.4	63.9	79.3	78.2	89.6	78.8	98.4	56.5	63.8	85.7	60.3	63.8	85.5	52.7	39.4	72.1
Night	HRNet	95.4	78.1	86.8	46.5	41.6	59.1	65.8	65.2	77.2	42.0	86.2	66.2	40.1	80.5	16.6	31.0	86.2	37.1	49.2	60.6
	OVeNet	95.6	79.4	87.4	48.5	42.3	61.1	68.2	69.9	78.1	43.8	86.4	68.6	44.4	82.0	10.9	44.3	87.3	43.3	51.3	62.8
Rain	HRNet	95.7	83.9	93.6	60.2	62.7	70.1	80.9	79.7	94.4	51.9	98.7	72.4	18.7	92.5	67.0	85.3	87.3	50.9	66.4	74.5
	OVeNet	96.4	86.5	94.3	65.2	64.6	72.6	83.6	82.2	94.6	54.3	98.7	76.4	21.8	93.4	75.7	88.9	89.1	50.9	66.4	76.6
Snow	HRNet	95.0	79.6	91.4	49.6	58.2	69.7	86.6	78.6	92.9	59.4	97.9	77.2	24.5	91.7	53.4	56.2	90.1	39.8	66.8	71.5
	OVeNet	95.7	81.9	92.4	55.3	59.8	71.9	88.1	80.5	93.4	60.7	98.0	79.8	25.7	92.7	59.6	65.4	91.6	45.2	70.3	74.1
All	HRNet	95.3	80.3	90.5	52.0	53.1	65.1	78.2	74.2	89.2	68.4	96.7	70.6	36.1	88.2	55.9	54.3	88.0	43.8	58.9	70.5
	OVeNet	95.8	82.1	91.3	55.8	54.6	67.6	80.5	77.3	89.7	69.5	96.8	73.4	39.1	89.5	61.9	65.0	89.4	47.2	60.6	73.0

ated 7 different variations on Cityscapes. The performance of each model variation in relation to the ground truth images was calculated by means of the mIoU (as defined above). At first, we initialized both heads of the network with the pre-trained Imagenet weights and set the offset vector length equal to 0.5. Secondly, we froze both main body's and initial head's weights. The frozen part of our model was initialized with the corresponding Cityscapes final pre-trained weights. The only part trained was the second head, which was initialized with pre-trained ImageNet weights. As shown in Table 5, although the performance of our model is higher than the initial single head model's one, it still remains lower than the case where both heads are trained simultaneously. Then, we deactivated the "Frozen" feature and changed the offset vector's length logarithmically, setting both the values 1 and 0.2. We observed that in both cases the performance is lower than that of 0.5. This is due to the fact that larger offset vectors point to more distant objects that may affect erroneously the final prediction, while smaller vectors do not exploit too much information from neighbouring classes. Furthermore, we deactivated the OHem Cross Entropy Loss and enabled the simple Cross Entropy Loss. As expected, the performance of the model was lower. OHem penalizes more high loss values and leads to a better training of the model. Lastly, HRNet [74] consists of 4 stages. In all the previous cases, the branch occurred on the last (4^{th}) stage so as not to overload the new network with many extra parameters. When the branch occurred on the 3^{rd} stage the performance did not become better.

5. Conclusion

All in all, we have presented a supervised method for semantic segmentation which selectively exploits information from neighboring pixels. OVeNet has enhanced by far the initial model's output predictions, since it has achieved not only better total results but also better per class results

Table 4. **Comparison of the models on different conditions of ACDC.**

Method	Fog	Night	Rain	Snow	All
RefineNet [45]	65.7	55.5	68.7	65.9	65.3
DeepLabv2 [12]	54.5	45.3	59.3	57.1	55.3
DeepLabv3+ [15]	69.1	60.9	74.1	69.6	70.0
HRNet [74]	69.3	60.6	74.5	71.5	70.5
OVeNet	72.1	62.8	76.6	74.1	73.0

Table 5. **Ablation study of components of our method.** "Fr:" Freezed main body's and initial head's weights and initialize them with Cityscapes final pre-trained weights, "Br:" Branch, " τ ": Offset Vector Length, "OHem": OHem Cross Entropy.

Fr	Br	τ	OHem	mIoU
			✓	81.83
	4	0.5	✓	82.40
✓	4	0.5	✓	82.01
	4	1	✓	81.79
	4	0.2	✓	82.30
	4	0.2		81.96
	3	0.2	✓	82.20

in the majority of classes under similar training time. It has learned an implicit representation of different objects which benefits the overall semantic segmentation estimation capability of the network. In fact, not only our idea has achieved highly satisfactory results close to GT images, but also has outperformed the predictions outputted by the initial model's head. Classifying some false predicted pixels in the correct classes, it has eliminated discontinuities and improved the shape as well as the form of the corresponding segments, leading to more realistic results. This is a strong contribution which opens new pathways for real world applications, such as self-driving cars or medical imaging and diagnostics.

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A. Network Instantiation

OVeNet follows the same general architecture as [74]. Since it is built on HRNet [74], our network contains four stages and two heads, as shown in Table 6. The branch occurs on the 4th stage. The semantic head of our model is constructed from modularized blocks, which are repeated a specific number of times in each of the four stages. In particular, the blocks are repeated 1, 1, 4, and 3 times, respectively, following the same configuration as the original HRNet model. However, in the offset head, we had to make a modification to the number of block repetitions in order to address memory constraints. As a result, the blocks are repeated 2 times in the 4th stage of the offset head. Each modularized block in our network consists of 1, 2, 3, or 4 branches, depending on the stage in which it is located (1st, 2nd, 3rd, or 4th). Each branch is associated with a different resolution and is composed of four residual units and one multi-resolution fusion unit.

B. Additional Qualitative Results

We provide additional qualitative comparisons of OVeNet to its HRNet baseline for the two examined datasets: Cityscapes [19] and ACDC [65]. More specifically, we provide sets of successful segmentations in Fig. 5 and 6 and sets of challenging and failure cases in Fig. 7 and 8 correspondingly.

In Fig. 5 we depict the successful results on Cityscapes. We also present an additional comparison of the default instance of OVeNet built only on HRNet [74] with the instance of OVeNet built on HRNet+OCR [87]. As we can see, OVeNet (*HRNet*) reduces correctly the number of misclassified terrain pixels on the right side of the road in the 3rd row of Fig. 5. On the other hand, OVeNet (*HRNet* + *OCR*) achieves a better prediction since it enlarges the sidewalk segment and it eliminates the terrain. Regarding the 6th row, OVeNet (*HRNet*) expands the terrain on the right, while the HRNet + OCR-based model increases additionally the sidewalk segment in the background. Overall, the latter generally achieves better predictions than the former.

In Fig. 6 we observe the results of successful segmentations on ACDC, where HRNet [74] is compared to OVeNet built only on it. Specifically, in the 2nd as well as the 7th row of Fig. 6, OVeNet enhances the prediction made by HRNet in the sidewalk on the right. A similar result happens with the terrain segment in the 5th row, as it covers correctly all the more space. Thus, our model surpasses baseline’s performance on adverse conditions.

As for Fig. 7, we provide some challenging cases on Cityscapes. To be more specific, we can see that in both rows, HRNet [74] results in a better prediction than OVeNet (*HRNet*) (e.g car on the left in the 1st row, terrain on the right in the 2nd one). On the other hand, OVeNet (*HR-*

Net + *OCR*) outperforms both the HRNet and HRNet-based model, leading to a better total outcome.

Regarding Fig. 8, we see some failure cases of our model built on HRNet [74] on ACDC. Specifically, in both rows, there are more correctly predicted labels in the vegetation segment on the right outputted by HRNet than by OVeNet.

All in all, we observe that OVeNet not only produces results that are very faithful to ground-truth annotations, but its predictions also surpass the predictions made by the initial HRNet in terms of quality. By correctly classifying several pixels which are misclassified by the HRNet baselines, OVeNet (*HRNet* + *OCR*) eliminates inconsistencies and enhances the shape and appearance of respective segments, resulting in more realistic outputs.

Table 6. **The architecture of the OVeNet (main body).** Within each cell of our network, there are three distinct components. The first component, represented by $[\cdot]$, refers to the residual unit. The second component is a numerical value that specifies the number of times the residual unit is repeated. The final component is another numerical value that indicates how many times the modularized block is repeated within the cell. In each residual unit, the variable C is used to represent the number of channels.

Head	Resolution	Stage 1	Stage 2	Stage 3	Stage 4
Semantic	4×	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 4 \times 1$	$\begin{bmatrix} 3 \times 3, C \\ 3 \times 3, C \end{bmatrix} \times 4 \times 1$	$\begin{bmatrix} 3 \times 3, C \\ 3 \times 3, C \end{bmatrix} \times 4 \times 4$	$\begin{bmatrix} 3 \times 3, C \\ 3 \times 3, C \end{bmatrix} \times 4 \times 3$
	8×		$\begin{bmatrix} 3 \times 3, 2C \\ 3 \times 3, 2C \end{bmatrix} \times 4 \times 1$	$\begin{bmatrix} 3 \times 3, 2C \\ 3 \times 3, 2C \end{bmatrix} \times 4 \times 4$	$\begin{bmatrix} 3 \times 3, 2C \\ 3 \times 3, 2C \end{bmatrix} \times 4 \times 3$
	16×			$\begin{bmatrix} 3 \times 3, 4C \\ 3 \times 3, 4C \end{bmatrix} \times 4 \times 4$	$\begin{bmatrix} 3 \times 3, 4C \\ 3 \times 3, 4C \end{bmatrix} \times 4 \times 3$
	32×				$\begin{bmatrix} 3 \times 3, 8C \\ 3 \times 3, 8C \end{bmatrix} \times 4 \times 3$
Offset Vector	4×				$\begin{bmatrix} 3 \times 3, C \\ 3 \times 3, C \end{bmatrix} \times 4 \times 2$
	8×				$\begin{bmatrix} 3 \times 3, 2C \\ 3 \times 3, 2C \end{bmatrix} \times 4 \times 2$
	16×				$\begin{bmatrix} 3 \times 3, 4C \\ 3 \times 3, 4C \end{bmatrix} \times 4 \times 2$
	32×				$\begin{bmatrix} 3 \times 3, 8C \\ 3 \times 3, 8C \end{bmatrix} \times 4 \times 2$

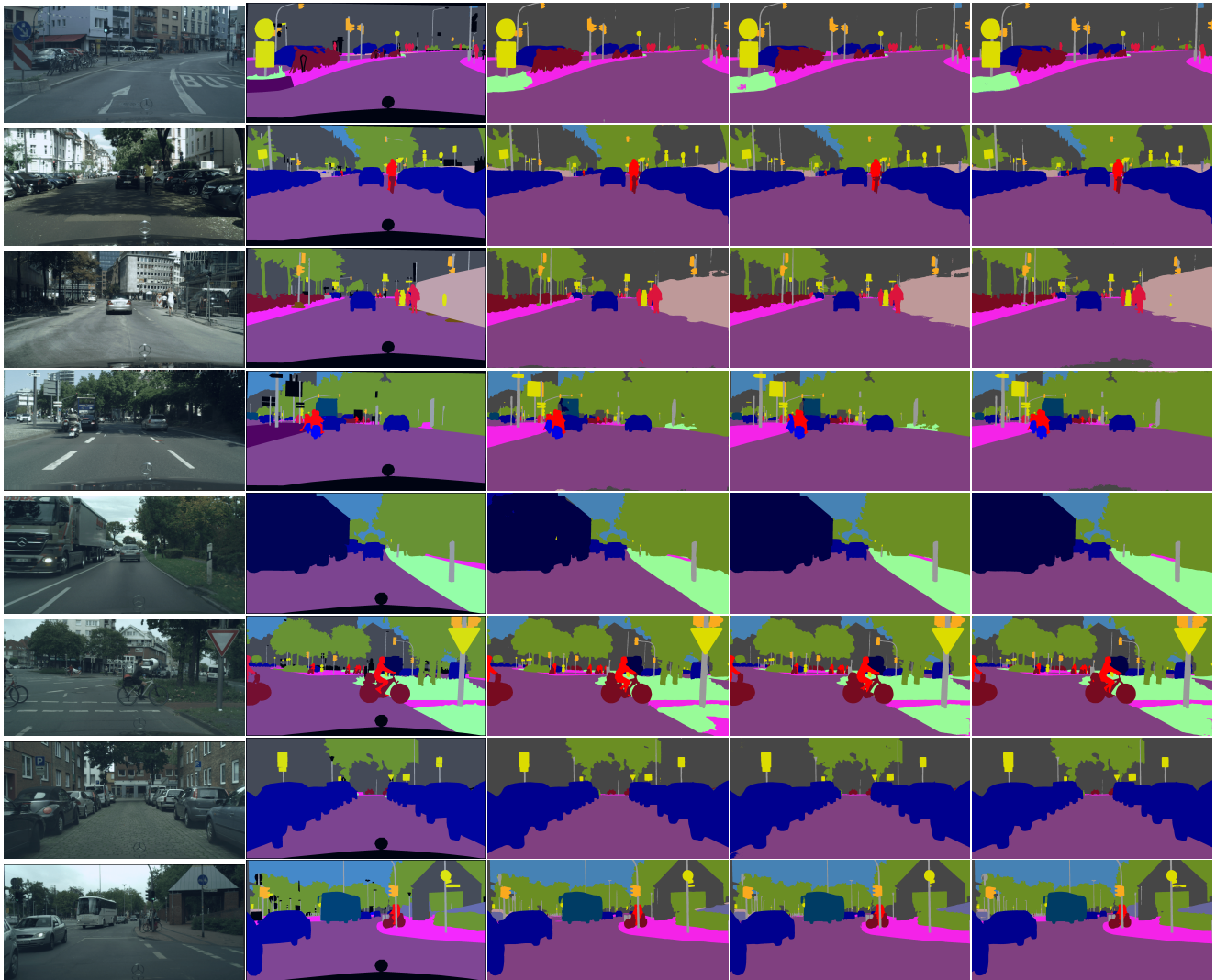


Figure 5. **Additional qualitative results of selected examples on Cityscapes.** From left to right: input image, ground-truth annotation, and prediction with HRNet [74], OVeNet (*HRNet*), and OVeNet (*HRNet+OCR*). Best viewed on a screen and zoomed in.

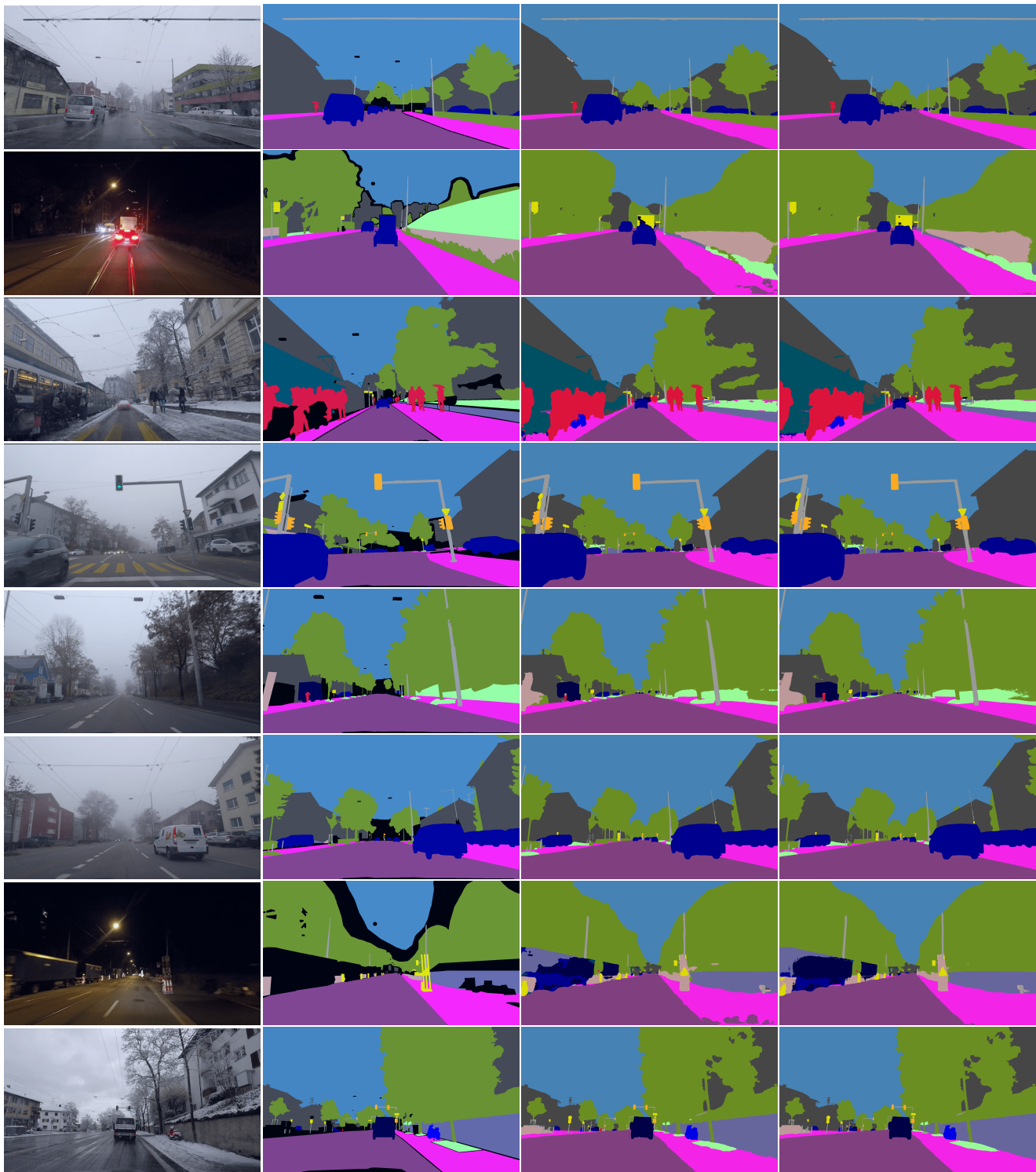


Figure 6. **Additional qualitative results of selected examples on ACDC.** From left to right: input image, ground-truth annotation, and prediction with HRNet [74] and OVeNet. Best viewed on a screen and zoomed in.

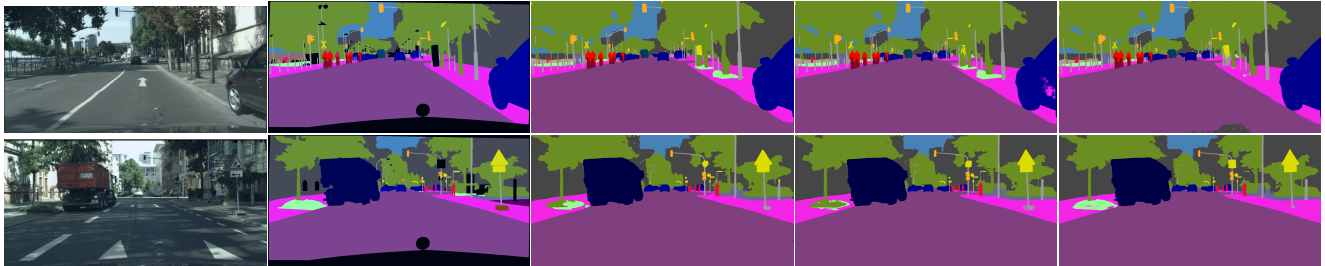


Figure 7. **Challenging cases on Cityscapes.** From left to right: input image, ground-truth annotation, and prediction with HRNet [74], OVeNet (*HRNet*), and OVeNet (*HRNet+OCR*). Best viewed on a screen and zoomed in.

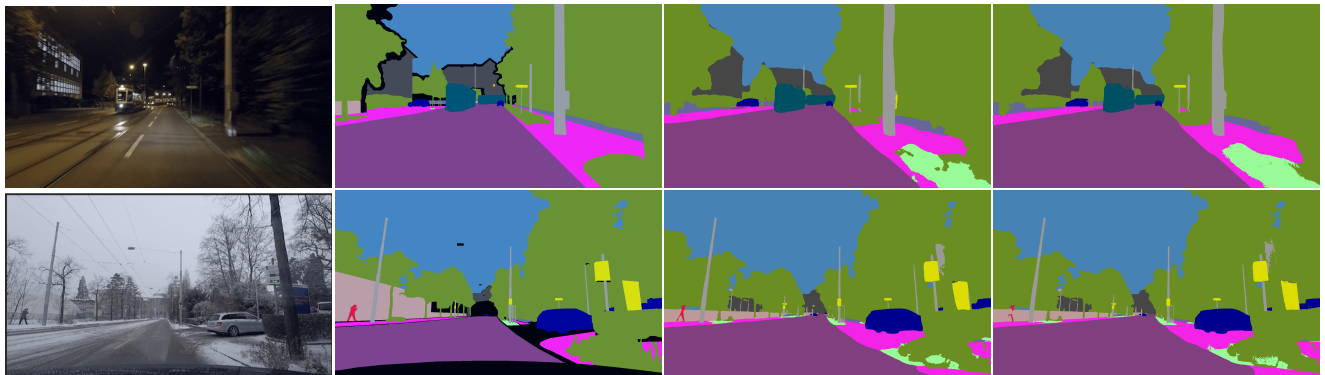


Figure 8. **Failure cases on ACDC.** From left to right: input image, ground-truth annotation, and prediction with HRNet [74] and OVeNet. Best viewed on a screen and zoomed in.