DensePASS: Dense Panoramic Semantic Segmentation via Unsupervised Domain Adaptation with Attention-Augmented Context Exchange

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Abstract—Intelligent vehicles clearly benefit from the expanded Field of View (FoV) of the 360° sensors, but the vast majority of available semantic segmentation training images are captured with pinhole cameras. In this work, we look at this problem through the lens of domain adaptation and bring panoramic semantic segmentation to a setting, where labelled training data originates from a different distribution of conventional pinhole camera images. First, we formalize the task of unsupervised domain adaptation for panoramic semantic segmentation, where a network trained on labelled examples from the source domain of pinhole camera data is deployed in a different target domain of panoramic images, for which no labels are available. To validate this idea, we collect and publicly release DensePASS - a novel densely annotated dataset for panoramic segmentation under cross-domain conditions, specifically built to study the PINHOLE → PANORAMIC transfer and accompanied with pinhole camera training examples obtained from Cityscapes. DensePASS covers both, labelled- and unlabelled 360° images, with the labelled data comprising 19 classes which explicitly fit the categories available in the source domain (i.e. pinhole) data. To meet the challenge of domain shift, we leverage the current progress of attention-based mechanisms and build a generic framework for cross-domain panoramic semantic segmentation based on different variants of attention-augmented domain adaptation modules. Our framework facilitates information exchange at local- and global levels when learning the domain correspondences and improves the domain adaptation performance of two standard segmentation networks by 6.05% and 11.26% in Mean IoU.

I. INTRODUCTION

Semantic segmentation is essential for perception of intelligent vehicles as it enables to locate key entities of a driving scene, such as road, sidewalk or person, by assigning a category label to every image pixel. While semantic segmentation results have increased at a rapid pace since the emergence of fully convolutional networks [1], most of the previous frameworks are developed under the assumption that the images are captured with a pinhole camera. However, the comparably narrow Field of View (FoV) largely limits the perception capacity and can be addressed by mounting multiple sensors, which, in return, requires additional mechanisms for data fusion [2]. Recently, leveraging a single panoramic camera, which offers a unified 360° perception of the driving environment, started to gain attention as a novel alternative for expanding the FoV [3].

Unfortunately, the scarcity of pixel-wise annotation of panoramic images still hinders the progress in the semantic segmentation community. At the same time, domain adaptation becomes an increasingly popular research topic, giving a new perspective to complement the insufficient coverage of training data in driving scenarios, e.g., at the nighttime [4] or in accident scenes [5]. In this paper, we argue that panoramic segmentation might strongly benefit from the significantly larger datasets available in the domain of standard image segmentation and explore domain adaptation techniques for such knowledge transfer. Thereby, we formalize the task of unsupervised domain adaptation for panoramic segmentation in a novel Dense PAnoramic Semantic Segmentation (DensePASS) benchmark, where images in the label-scarce panoramic target domain are handled by adapting from data of the label-rich pinhole source domain.

We aim to promote research of panoramic semantic segmentation under cross-domain conditions and introduce DensePASS – a new dataset with panoramic images collected all around the globe to encourage diversity. To enable credible quantitative evaluation, our benchmark comprises (1) an unlabelled panoramic training set used for optimization
of the domain adaptation model and (2) a panoramic test set manually labelled with 19 classes defined in accordance to Cityscapes [6], a dataset with pinhole images which we use as training data in the label-rich source domain. Yet, a straightforward transfer of models trained on pinhole images to panoramic data often results in a significant performance drop, since the layout of the panoramic camera images passed through the equirectangular projection strongly differs from the standard pinhole camera data. For example, as shown in Fig. 1, panoramic images have longer horizontal distribution or geometric distortion on both sides of the viewing direction, resulting in a considerable domain shift.

To effectively utilize label-rich pinhole image datasets [6], [7] for label-scarce panoramic segmentation, we systematically examine different Domain Adaptation (DA) strategies for the Pinhole to Panoramic Domain Adaptation (P2PDA) (the formalized P2PDA task illustrated in Fig. 2). Furthermore, we implement a P2PDA framework with different DA mechanisms: (i) Segmentation Domain Adaptation Module (SDAM), (ii) Attentional Domain Adaptation Module (ADAM), and (iii) Regional Context Domain Adaptation Module (RCDAM). The proposed SDAM module allows greater flexibility than the previous DA methods [8], [9] used in the output space as it can be plugged in at different feature levels. Another challenge is learning good feature representations, which is not only distinguishing various categories with similar appearances, but also linking the same category at diverse locations across the 360°. To address this, we leverage the progress of attention-based models [10], [11], [12] and propose the ADAM module for capturing long-range dependencies and positional relations. Lastly, the RCDAM module addresses the horizontal distribution of panoramic images and obtains region-level context in order to effectively resist the geometric distortion caused by the equirectangular projection. Extensive experiments demonstrate the effectiveness of our framework, exceeding more than 15 state-of-the-art semantic segmentation methods.

In summary, our main contributions are as following:

- We create and publicly release DensePASS – a new benchmark for panoramic semantic segmentation collected from locations all around the world and densely annotated with 19 classes in accordance to the pinhole camera dataset Cityscapes to enable proper PINHOLE→PANORAMIC evaluation.
- We formalize the problem of unsupervised domain adaptation for panoramic segmentation focused on transfer from label-rich pinhole datasets to DensePASS.
- We propose a generic P2PDA framework and investigate different DA modules both in a separate and joint manner, validating their effectiveness with various networks designed for self-driving scene segmentation.

II. RELATED WORK

A. Semantic Segmentation and Self-attention Modules

The performance of semantic segmentation models has rapidly improved through the explosive rise of deep learning [1], [13], [14], [15]. The first prominent end-to-end architecture to outperform conventional approaches was the Fully Convolutional Network (FCN) [1] followed by DeepLab [13], PSPNet [14] and DenseASPP [15] leveraging atrous convolutions or pyramid pooling.

At the same time, the use of self-attention modules [16], which learn to automatically weigh input positions (i.e. temporal [16] or spatial [10]), increasingly gains interest in the field. Such mechanisms are widely used for capturing long-range contextual dependencies which are crucial for dense prediction tasks. The success of attention mechanisms in visual recognition [10], leads to their explorations in some semantic segmentation works focused on both, accuracy-oriented networks [11], [17], [18] and efficiency-oriented networks [12], [19], [20]. For example, FANet [12] proposed a fast self-attention module for non-local context aggregation aiming efficient segmentation, whereas DANet [11] was designed with position and channel attention modules to learn spatial and channel interdependencies.

We leverage such attention principles to mitigate the domain shift by highlighting regional context and present a cross-domain segmentation framework with attentional domain adaptation modules. We experiment with both, accuracy- and efficient-oriented networks [11], [12], [21] as the segmentation architecture, and demonstrate the consistent effectiveness of our adaptation modules for bringing standard semantic segmentation model to panoramic imagery.

B. Semantic Segmentation for Panoramic Images

Segmentation of panoramic data, which is often captured through distortion-heavy fisheye lenses [22], [23] or multiple cameras [2], [24], is especially challenging as it requires eliminating distortions, synchronizing and calibrating the cameras, and fusing the data, which leads to higher latency. Yang et al. introduced the PASS [3] and the DS-PASS [25] frameworks which successfully mitigate the effect of distortions by using a panoramic annular lens system but come with a high memory- and computational cost. This was significantly improved by the O OSS framework [26] through multi-source omni-supervised learning for omnidirectional segmentation. The latest advancements include frameworks focusing on omni-range contextual dependencies [19] or leveraging pixel-level contrastive pre-training [27].

All previous frameworks [3], [19], [27] are developed under the assumption that the labelled training data are implicitly or partially available in our target domain of panoramic images. Since panoramic datasets are comparably small in size, we argue, that panoramic segmentation might strongly benefit from the significantly larger datasets available in the domain of standard image segmentation. To achieve this, we look at panoramic segmentation from a domain adaptation perspective and introduce the DensePASS dataset covering images with 19 annotated categories in both, standard- and panoramic domains. We further introduce a framework for unsupervised domain adaptation for panoramic semantic segmentation, where we combine prominent segmentation approaches with attention-based adaptation modules.
C. Domain Adaptation for Semantic Segmentation

Domain adaptation has been recently addressed in the standard semantic segmentation, by either (1) optimizing the source domain networks on pseudo-labels generated by a model trained in the source domain [28], [29], or (2) leveraging a Generative Adversarial Network (GAN) [30] to learn domain translations [4], [8], [9], [31]. To utilize the significant amount of source-target similarities in the resulting segmentation masks, Tsai et al. [8] aligned the domains in output space via adversarial learning (AdaptSegNet). Chang et al. [9] introduced the DISE framework which extracts domain-invariant structure and domain-specific texture information to reduce the source-target discrepancies. Attention mechanisms also started gaining attention for domain adaptation with techniques such as attentional transfer [32] or multiple cross-domain attention modules for obtaining context dependencies from both local and global perspectives [33].

We specifically focus on domain transfer for panoramic semantic segmentation, which differs from the standard pinhole images in several important aspects, such as discontinuous boundaries and distorted objects. To capture long-range correlations between pixels and semantic regions, we extend AdaptSegNet [8] with attention-augmented modules in multiple stages and a regional context exchange, leading to a significant adaptation improvement.

III. P2PDA: PROPOSED FRAMEWORK

In this work, we introduce a generic framework for 360° perception of self-driving scenes by learning to adapt semantic segmentation networks from a label-rich source domain of standard pinhole camera images to the unlabelled target domain of panoramic data. Conceptually, our framework comprises encoder-decoder-based semantic segmentation network and three different building blocks for domain alignment: Segmentation domain adaptation module (SDAM), Attentional domain adaptation module (ADAM) and Regional context domain adaptation module (RCDAM), which we place at two different network stages: after and before the decoder of the segmentation network (denoted as DA_2 and DA_1 respectively). Next, we present an overview of the proposed framework (Sec. III-A) and describe the three integrated domain adaptation modules in detail (Sec. III-B).

A. Framework Overview

Our framework builds on the AdaptSegNet model [8], extending it with multiple versions of region- or attention-augmented DA modules placed at different network levels with an overview provided in Fig. 3. The main components of our framework are a weight-shared segmentation network \( G \) with attention modules and two DA modules (DA_2 and DA_1) with corresponding discriminators \( D \). We denote the source domain images as \( I_s \) and target domain images as \( I_t \).

For simplicity, \( I_s \) and \( I_t \) also refer to the intermediate feature map representations of the images.

At first, the source domain images \( I_s \) are fed into the segmentation network \( G \) (also referred to as the generator) to generate prediction results and the source ground-truth labels are used to compute the segmentation loss \( L_{seg} \). Next, the corresponding feature maps are passed to the domain adaptation modules in order to close the gap between the source and target domains at different network levels. The discriminators are trained with the binary objective to estimate the domain of the input data, so that the discriminator loss \( L_D(I_s, I_t) \) is a cross-entropy loss with two classes (panoramic and pinhole).

The discriminator output of the target domain data \( I_t \) is directly used to estimate the adversarial loss \( L_{adv}[D(I_t)] \) for the generator training (alongside with \( L_{seg} \)) and is high if the discriminator prediction is correct (so the adversarial loss facilitates generation of segmentation masks in the target domain which successfully “fool” the discriminator). In other words, the discriminators are trained to distinguish between the source and target domains with \( L_D(I_s, I_t) \), while the segmentation network \( G \) is trained to 1) correctly segment the images from the source domain with \( L_{seg} \), and 2) “fool” the discriminator by making the target domain data indistinguishable from the source domain data. The final loss
used to train the generator becomes:

\[ L_G(I_s, I_t) = \lambda_{seg} L_{seg}(I_s) + \lambda_{adv} L_{adv}[D(I_t)], \]

where \( \lambda_{adv} \) and \( \lambda_{seg} \) are weights used to balance the domain adaptation and semantic segmentation losses.

### B. Domain Adaptation Modules

We now explain the three integrated DA modules in detail.

**Segmentation domain adaptation module (SDAM).** Our initial domain adaptation module SDAM is derived from AdaptSegNet and attempts to align the segmentation output of the source and target maps (the module is illustrated in Fig. 4). After a segmentation network forward pass with both, an image from the source and target domains \((I_s, I_t)\), feature maps of the both representations are used as input to the discriminator \(D\) which learns to predict the domain with \(L_D(I_s, I_t)\), while the segmentation network \(G\) learns to correctly segment the pinhole images with \(L_{seg}(I_s)\) and align the domains with \(L_{adv}[D(I_t)]\). The SDAM learns a PINHOLE→PANORAMIC domain adaptation model at multiple levels jointly (i.e. integration in DA_1 and DA_2).

**Attentional domain adaptation module (ADAM).** To detect and effectively utilize the significant amount of pinhole-panoramic correspondences at both, local and global scale, we design ADAM, an attntional domain adaptation module (overview in Fig. 5). ADAM differs from SDAM as it leverages the attention mechanism to learn an optimal weighting scheme for the features used as the discriminator input. By doing this, ADAM enables direct information exchange among all pixels, mitigating the influence of discrepancy in positional priors and local distortions. Relevant portions of the feature maps of both, \(I_s\) and \(I_t\) inputs are magnified through the attention and the re-weighted source and target representations are both used to optimize the corresponding discriminator \(D\) with adversarial loss. Since ADAM operates on attended feature maps with long-range contextual dependency aggregation, it is used in DA_2 only.

**Regional context domain adaptation module (RCDAM).** Next, we focus on region relationship of the panoramic images. Inspired by RANet [17], we design the RCDAM module to configure the information flow between different regions and within the same region, as illustrated in Fig. 6. RCDAM follows a hierarchical adversarial learning scheme with two-stage discriminators, where the first stage is identical to the previously described SDAM. The second stage covers two blocks: a Region Construction Block (RCB) and a Region Interaction Block (RIB) first introduced in RANet. The inputs to this stage are the feature maps of \(I_s\) and \(I_t\) after a segmentation network forward pass.

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TABLE I. Per-class results on DensePASS. We use FANet [12] as the segmentation network and set different domain adaptation modules for DA_2 and DA_1 to test our methods on DensePASS with the size of input 2048×400. S represents the segmentation domain adaptation module, A represents the attentional domain adaptation module and S+A represents a combination of S and A. The first line is the Cityscapes source-only result without adaptation.

| Methods  | DA_2          | DA_1          |
|----------|---------------|---------------|
|          | Mean IoU      | Mean IoU      |
|          | building     | road          |
|          | wall          | pole          |
|          | traffic light | traffic sign  |
|          | vegetation    | sky           |
|          | person        | rider         |
|          | car           | truck         |
|          | bus           | train         |
|          | motorcycle    | bicycle       |
| FANet    | -             | -             |
|          | 26.90         | 62.98         |
|          | 10.64         | 72.41         |
|          | 8.20          | 20.74         |
|          | 11.77         | 6.85          |
|          | 3.75          | 68.11         |
|          | 21.56         | 87.00         |
|          | 23.73         | 5.33          |
|          | 49.61         | 10.65         |
|          | 0.54          | 16.76         |
|          | 24.15         | 6.62          |
| FANet    | S             | S             |
|          | 32.17         | 62.16         |
|          | 16.85         | 78.78         |
|          | 13.67         | 24.07         |
|          | 19.72         | 11.42         |
|          | 9.68          | 71.42         |
|          | 18.22         | 85.72         |
|          | 32.66         | 11.75         |
|          | 54.34         | 17.61         |
|          | 0.00          | 41.52         |
|          | 29.30         | 12.30         |
| FANet    | A             | S             |
|          | 32.67         | 62.28         |
|          | 16.86         | 79.99         |
|          | 17.64         | 23.96         |
|          | 19.78         | 12.33         |
|          | 9.58          | 72.01         |
|          | 19.29         | 85.91         |
|          | 32.85         | 11.03         |
|          | 6.85          | 72.41         |
|          | 17.61         | 87.00         |
|          | 55.75         | 15.38         |
|          | 0.38          | 43.53         |
|          | 29.19         | 12.95         |
| FANet    | S+A           | S             |
|          | 33.05         | 61.74         |
|          | 17.70         | 80.00         |
|          | 16.38         | 24.64         |
|          | 19.61         | 12.04         |
|          | 9.79          | 72.27         |
|          | 17.94         | 86.31         |
|          | 33.17         | 11.47         |
|          | 55.18         | 15.61         |
|          | 0.04          | 52.55         |
|          | 28.68         | 12.82         |

regional context. Thereby, the final output is from the first stage, which means this domain adaptation module does not change the original architecture of the segmentation network and can be used for networks without attention layers.

IV. NEW BENCHMARK AND EXPERIMENTS

To evaluate the idea of panoramic segmentation through domain adaptation from standard pinhole camera images, we conduct extensive experiments with different variants of our P2PDA framework. First, we introduce the novel DensePASS dataset for dense panaromic segmentation of driving scenes annotated in accordance to the pinhole camera dataset Cityscapes (Sec. [IV-A]). Then, we quantitatively validate how well the P2PDA framework can handle the PINHOLE→PANORAMIC transfer and conduct extensive ablation studies for different versions of DA modules and two segmentation networks: the speed-oriented FANet [12] (Sec. [IV-B]) and accuracy-oriented DANet [11] (Sec. [IV-C]). We further benchmark our framework against more than 15 state-of-the-art segmentation models (Sec. [IV-D]) and examine the impact of expanding the training data with another source dataset (Sec. [IV-E]). Finally, we showcase multiple qualitative examples of the achieved results (Sec. [IV-F]). We adopt Mean Intersection over Union (IoU) as our main evaluation metric.

A. Dataset and Experimental Settings

Source dataset (pinhole). We use Cityscapes [6] as our label-rich source dataset providing a large amount of annotated pinhole camera images. Cityscapes covers 2979 training- and 500 validation examples captured in 50 different European cities and annotated with 19 categories. We use the 2979 training samples as our source training data.

DensePASS target dataset (panoramic). Since no established segmentation benchmarks target the PINHOLE→PANORAMIC transfer and previous panoramic test-beds cover a very small number of classes [3][19], we collect DensePASS – a novel densely annotated dataset for panoramic segmentation of driving scenes. While DensePASS could also be used for the the same-domain panaromic segmentation, it is specifically built with the PINHOLE→PANORAMIC transfer in mind, so that the test data is annotated with 19 categories present in the paninole camera dataset Cityscapes. To facilitate the unsupervised domain adaptation task, DensePASS covers both, labelled data (100 panoramic images used for testing) and unlabelled training data (2000 panoramic images used for the domain transfer optimization). Panoramic images (2048×400 resolution) are collected using Google Street View, spanning images from different continents (25 different cities for testing and 40 for training).

Training settings. We use stochastic gradient descent (initial learning rate of 1e−5, momentum of 0.9 and a decay of 5e−4) for optimization of the segmentation network G and the Adam optimizer for discriminators D (initial learning rate set to 4e−6). For both optimizers, the learning rate is decreased polynomially where the learning rate is multiplied by (1−\(\frac{\text{iter}}{\text{max\_iter}}\))\(^0.9\) after each iteration, where max_iter is set to 200000 with a batch-size of 2. The loss balancing weights, \(\lambda_{adv}\) and \(\lambda_{seg}\) are set to 0.001 and 1.0 for DA_1, and 0.0002 and 0.1 for DA_2. In the RCDAM module, \(\lambda_{seg}\) is set to 1.5 for the prediction result before RCB. During training, pinhole images are resized to 1280×720 while panoramic data is kept at the 2048×400 resolution.

B. Ablation Studies for Segmentation Network with FANet

We first consider FANet [12], a lightweight speed-oriented network, as the segmentation model and investigate different combinations of domain adaptation modules for DA_2 and DA_1. As shown in Table [I] before adaptation, FANet yields a mean IoU of 26.90% indicating large room for improvement in cross-domain generalization. Our framework improves the result to 32.17% by using the SDAM module in both DA_2 and DA_1 (5.27% gain). Integrating the attentional ADAM module also leads to a considerable boost (32.67% IOU, a 5.77% gain over the the source-only baseline). A combination of the SDAM and ADAM modules in DA_2 yields the best recognition result of 33.05% IoU.

C. Ablation Studies for Segmentation Network with DANet

Next, we experiment with a heavier and more accuracy-oriented segmentation network DANet [11] (results provided in Table [I]). The native source-trained DANet achieves a mean IoU of only 28.50%, highlighting the sensitivity of modern segmentation networks to the PINHOLE→PANORAMIC domain shift. The performance is strongly improved (10.01% boost) through SDAM modules placed in DA_2 and DA_1, achieving 38.51% in mean IoU. Similarly, using the ADAM module in DA_2 yields a result of 39.16% (a 10.66% improvement over the source-only baseline). Combining both the SDAM and ADAM modules again slightly improves the performance (39.28% mean IoU).

We further explore the use of the RCDAM module in DA_1, yielding 39.46% mIoU (10.96% boost over the baseline). The best performance of 39.76% (11.26% boost with
TABLE II. Per-class results on DensePASS. We use DANet [11] as the segmentation network and set different domain adaptation modules for DA_2 and DA_1 to test our methods on DensePASS with the size of input 2048×400. S represents the segmentation domain adaptation module, A represents the attentional domain adaptation module, and R represents the regional context domain adaptation module and S+A represents a combination of S and A. The first line is the Cityscapes source-only result without adaptation. * denotes further adding source images from WildDash to complement Cityscapes.

| Methods       | DA_2         | DA_1         | Mean IoU | road | sidewalk | building | wall | fence | pole | traffic-light | traffic-sign | vegetation | sky | person | rider | car | truck | bus | train | motorcycle | bicycle |
|---------------|--------------|--------------|----------|------|----------|----------|------|-------|------|--------------|-------------|------------|-----|--------|-------|-----|-------|-----|-------|------------|---------|
| DAANet        | -            | -            | 79.6     | 29.08| 8.30     | 79.0     | 9.49 | 21.64 | 15.91| 5.85         | 9.26        | 71.08      | 31.50| 85.13  | 6.55  | 1.68| 53.48 | 24.91| 30.22 | 0.52       | 0.53    | 17.00 |
| DAANet S      | S            | S            | 79.4     | 28.99| 8.28     | 78.8     | 9.47 | 21.63 | 15.90| 5.85         | 9.25        | 71.05      | 31.50| 85.13  | 6.55  | 1.68| 53.48 | 24.91| 30.22 | 0.52       | 0.53    | 17.00 |
| DAANet A      | S            | S            | 79.4     | 28.99| 8.28     | 78.8     | 9.47 | 21.63 | 15.90| 5.85         | 9.25        | 71.05      | 31.50| 85.13  | 6.55  | 1.68| 53.48 | 24.91| 30.22 | 0.52       | 0.53    | 17.00 |
| DAANet S+S+A  | S+S+A        | S+S+A        | 79.4     | 28.99| 8.28     | 78.8     | 9.47 | 21.63 | 15.90| 5.85         | 9.25        | 71.05      | 31.50| 85.13  | 6.55  | 1.68| 53.48 | 24.91| 30.22 | 0.52       | 0.53    | 17.00 |
| DANet          | -            | -            | 79.3     | 29.88| 8.38     | 78.6     | 9.47 | 21.63 | 15.90| 5.85         | 9.25        | 71.05      | 31.50| 85.13  | 6.55  | 1.68| 53.48 | 24.91| 30.22 | 0.52       | 0.53    | 17.00 |

E. Complementing the Cityscapes Source with WildDash

Our next area of investigation is the impact of expanding the source data with a more complex dataset, since DensePASS contains highly composite scenes due to larger FoV, while Cityscapes is large but relatively simple. To achieve this, we leverage the WildDash dataset [7] with 4256 pinhole images, pixel-level annotations and more unstructured surroundings. As shown in the last two rows of Table III, we obtain better mIoU with the expanded training set, achieving 41.35% and 42.47% with different P2PDA variants. Interestingly, the IoUs of road, sidewalk, terrain, car, and train are significantly improved, which we link to the strong positional priors of these categories in structured urban scenes, while DensePASS and WildDash environment is more chaotic and unconstrained. Furthermore, direct comparison of the two P2PDA versions demonstrates the effectiveness of the attention-augmented adaptation strategy.

F. Qualitative Analysis

In our final study, we showcase multiple examples of representative qualitative results in Fig. 8. The segmentation boundaries of regions such as sky, building, and vegetation are clearly improved through the P2PDA strategy in every case, while sidewalk segmentation clearly benefits from domain adaptation in the second row example. At the same time, some misclassified categories are corrected after adaptation (e.g., car and truck in all examples). There is also more clarity as it comes to detailed segmentation of small objects, such as traffic light and traffic sign in the first and the second row, as well as pole in all rows. These qualitative examples consistently confirm the conclusions of our quantitative evaluation, highlighting the benefits of the proposed P2PDA strategy for 360° self-driving scene understanding through domain adaptation from pinhole camera data.
Semantic scene understanding is vital for autonomous driving but requires models which can deal with changes in data distribution. In this work, we introduced the new task of cross-domain semantic segmentation for panoramic driving scenes, which extends the standard panoramic segmentation with the premise of the training data originating from a different domain (e.g. pinhole camera images). First, we formulate the problem of unsupervised domain adaptation for panoramic segmentation and introduce the novel DensePASS dataset which we use to study the PINHOLE→PANORAMIC transfer. To meet the challenge of domain divergence, we developed a generic framework enhancing conventional segmentation algorithms with different domain adaptation modules. While our experiments demonstrate that cross-domain panoramic segmentation task is difficult for modern algorithms, our proposed domain-agnostic framework with attention-based domain adaptation modules consistently improves the results. Our dataset will be publicly released upon publication and we believe that DensePASS has strong potential to motivate the needed development of generalizable semantic segmentation models.

V. CONCLUSION

Semantic scene understanding is vital for autonomous driving but requires models which can deal with changes in data distribution. In this work, we introduced the new task of cross-domain semantic segmentation for panoramic driving scenes, which extends the standard panoramic segmentation with the premise of the training data originating from a different domain (e.g. pinhole camera images). First, we formulate the problem of unsupervised domain adaptation for panoramic segmentation and introduce the novel DensePASS dataset which we use to study the PINHOLE→PANORAMIC transfer. To meet the challenge of domain divergence, we developed a generic framework enhancing conventional segmentation algorithms with different domain adaptation modules. While our experiments demonstrate that cross-domain panoramic segmentation task is difficult for modern algorithms, our proposed domain-agnostic framework with attention-based domain adaptation modules consistently improves the results. Our dataset will be publicly released upon publication and we believe that DensePASS has strong potential to motivate the needed development of generalizable semantic segmentation models.

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