Source domain subset sampling for semi-supervised domain adaptation in semantic segmentation

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Abstract

In this paper, we introduce source domain subset sampling (SDSS) as a new perspective of semi-supervised domain adaptation. We propose domain adaptation by sampling and exploiting only a meaningful subset from source data for training. Our key assumption is that the entire source domain data may contain samples that are unhelpful for the adaptation. Therefore, the domain adaptation can benefit from a subset of source data composed solely of helpful and relevant samples. The proposed method effectively subsamples full source data to generate a small-scale meaningful subset. Therefore, training time is reduced, and performance is improved with our subsampled source data. To further verify the scalability of our method, we construct a new dataset called Ocean Ship, which comprises 500 real and 200K synthetic sample images with ground-truth labels. The SDSS achieved a state-of-the-art performance when applied on GTA5 → Cityscapes and SYNTHIA → Cityscapes public benchmark datasets and a 9.13 mIoU improvement on our Ocean Ship dataset over a baseline model.

1. Introduction

Semantic segmentation is one of the most important tasks in computer vision, which estimates the pixel-level semantic labels of an image. The performance of segmentation has been substantially improved with the recent advances in deep learning [2, 3, 11, 16, 27, 32, 45]. However, existing methods need to be trained on large-scale segmentation datasets [1, 5, 15], where the acquisition of accurate ground-truth (GT) labels often requires massive human labour and high costs. As a proxy to a real-world dataset, synthetic datasets, such as GTA5 [25] and SYNTHIA [28], have been proposed. These synthetic datasets provide images generated by various simulations, together with highly accurate pixel-level GT segmentation annotations. Although they have successfully resolved the data deficiency problem, a critical issue remains as the network trained on the source (i.e., synthetic) dataset poorly generalizes on the target (i.e., real-world) dataset due to the large domain gap between the datasets.

Domain adaptation (DA) has drawn the attention of researchers to reduce the domain gap between the source and target images. In particular, unsupervised domain adaptation (UDA) methods [18, 44, 46] aim to resolve the domain gap problem with the source and target images without any GT of the target images. Although UDA methods have shown promising results, it is still challenging to overcome the problem and achieve comparable performance to that of fully supervised methods [19] without any reliable guidance from the target domain. Moreover, semi-supervised domain adaptation (SSDA) methods exploit not only source domain data but also a few labelled target domain data during training [12, 13, 29, 36]. In this paper, we propose a new SSDA approach to eliminate irrelevant source domain samples and benefit from a subset of source domain data only containing samples highly relevant to the target domain. We argue that there exist irrelevant or even unhelpful samples in large-scale source domain data generated even with a carefully controlled data generation scenario. Fig. 1 shows examples of confusing source domain samples. Because of the unconstrained movements during the simulation, a vehicle is seen driving on the sidewalk (c.f, 1st row). Humans often perceive this area as a road because of its similar appearance to a road and their basic knowledge of its geometry. These types of confusing source domain samples may hinder the effective domain adaptation [4]. In other words, this phenomenon often results in confusing training samples that

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may mislead the training procedure.

Therefore, we present the source domain subset sampling (SDSS) method to exploit a subset of samples selected from the entire source domain data during training. The subset sampled through the proposed method is more relevant to the target domain, showing synergistic effects when combined with previous methods [29, 36]. The proposed approach eliminates the aforementioned confusing samples and ensures that the training process facilitates only relevant and useful samples, as depicted in Fig. 1 (c).

We first utilized a small number of target data with GT labels to pre-train a segmentation network. Then, we extracted pixel-level source samples from a source domain by eliminating source samples incorrectly predicted by the pre-trained network. Furthermore, we selected image-level source samples by simultaneously considering class balance and prediction correctness within an image. With our approach, a subset of source data providing class-balanced and target domain relevant information was obtained efficiently.

Experimental results on the GTA5 and SYNTHIA datasets show that our method is effective in achieving superior segmentation performance with a reduced number of source data and shorter training time. We further presented a new Ocean Ship dataset containing 500 real and 200K synthetic images and validated the proposed method on our dataset. Our contributions can be summarized as follows:

- We propose a novel SDSS method for semi-supervised domain adaptation.
- We propose an image-level sampling algorithm to further consider the class balance and prediction correctness of source samples.
- We presented a new Ocean Ship dataset with 500 real and 200K synthetic images.

2. Related Works

In this section, we describe existing DA methods and active learning methods to discuss the effect of data selection for training. In addition, we investigate how self-training methods are used in various tasks.

Domain adaptation. Among the numerous tasks of computer vision, the segmentation task is particularly time-consuming and expensive to produce labels.

To solve this problem, Richter et al. [25] suggested the use of synthetic data that can easily obtain labels through the use of GTA5 games. Since then, numerous UDA studies [18, 21, 37, 40, 44, 46] have been proposed to improve the performance by training only with labels of synthetic data without labels of real data. Furthermore, SSDA studies [12, 29, 36] have been proposed to additionally utilize a small amount of labelled target domain data together with a large amount of source domain data. However, previous works do not pay much attention on how to efficiently utilize large-scale source data to reduce computational costs while preserving or even improving segmentation performance on the target domain.

Active learning. Because labelling a large number of data is costly and time-consuming, active learning [17, 41, 43] has been proposed to extract samples that are helpful for further performance improvement among unlabelled data.
Active learning first trains a model with only a small amount of labelled target data and gradually increases the number of training data by selecting sample data to be labelled from a large-scale unlabelled data for further training. The motivation and training process of active learning is similar to our synthetic data sampling method. However, our method has two major differences from the existing active learning: i) Active learning uses all unlabelled real data, but we only use a small amount of labelled real data. ii) Active learning does not use synthetic data, so there is no need to solve the domain difference problem. However, we need to solve the domain difference problem because we sample labelled synthetic data with a small amount of labelled real data.

**Self-training.** The self-training method is widely used in various computer vision tasks. For example, various self-training methods [14, 18, 44, 46] have achieved state-of-the-art performance in UDA for semantic segmentation. These methods improve their performance by creating pseudo-labels on unlabelled real data with a model trained on labelled synthetic data. In knowledge distillation [9, 22], self-training compresses the amount of computation and parameters while maintaining the same performance. It is also proven to be effective to deal with label noise with pseudo-labels [33, 38].

**Our work.** Different from previous works, we propose a source domain data sampling method that selects samples that can be beneficial to improve the target domain performance of the segmentation model. Our sampling method benefits from the knowledge learned from a small amount of labelled target domain data. The proposed method can be seamlessly combined with existing SSDA methods [29, 36]. As a result, with the reduced number of source domain data, we achieve a shorter training time and improved segmentation performance.

### 3. Source Domain Subset Sampling

The proposed SDSS method follows the semi-supervised domain adaptation (SSDA) configuration. The SSDA configuration allows access to large-scale labelled source domain data and a few labelled target domain data. Let $D_S = \{(x_i^s, y_i^s)\}_{i=1}^{N_S}$ and $D_T = \{(x_i^t, y_i^t)\}_{i=1}^{N_T}$ be the labelled source and target data where $x$ is an image, $y$ is a corresponding GT label and $N_S$ and $N_T$ denote the number of source and target data, respectively. SDSS aims to extract a subset $D_C = \{(x_i^c, y_i^c)\}_{i=1}^{N_C}$ of $D_S$ containing source domain samples highly relevant to the target domain. Fig. 2 shows the overall pipeline of the proposed method.

#### 3.1. Pixel-level sampling

One of the main reasons for performance degradation in DA is an inherent domain gap between the source and target domains. To minimize this domain gap, we refine source domain data in pixel-level based on the knowledge learned from the available small-scale target domain data. Therefore, we extract a pre-trained model biased to the target domain by training on a small amount of labelled data, as shown in stage 1 in Fig. 2. Then, as shown in stage 2 in Fig. 2, all source domains are predicted with the pre-trained model, and all, except the pixel information matching the GT of the source domain, is removed. Through this process, we can use the information of the source domain biased toward the target domain at the pixel-level.

Following [14], we first generated a pseudo-label $y_i^{SSL}$ of the pixel $i$ from the source domain for self-supervision as
Sea respectively, and your refined pseudo-labels not matched with the GT labels were eliminated to obtain labeled pseudo-labels. In other words, pseudo-labels that are corresponding GT class pairs were regarded as correct or otherwise depending on two thresholds: i) correctness confidence of each class, and ii) pixel ratio of each class in the image.

Our image scoring function in (3) considers two aspects: i) correctness ratio of each class, and ii) pixel ratio of each class in an image. The larger the ratio of the number of correctly classified pixels to that of the corresponding GT ones is (i.e., correctness ratio), the higher the image score is given. It is further adjusted based on the proportion of each class in the image where classes with a large portion of pixels will be given lower scores. With our method, an image containing a variety of classes and correct samples has a high chance to be utilized, whereas an image with imbalanced classes or a few number of available samples can be excluded easily for the training.

4. Experimental results

In this section, we present experimental results to validate the proposed sampling method for semantic segmentation. We first describe experimental configurations in detail. Then, we validate our SDSS on two public benchmark datasets, GTA5 [25] and SYNTHIA [28], and provide detailed analyses. Then, we verify and analyse the performance of our method on our new dataset called, Ocean Ship. Note that the Intersection-over-Union (IoU) metric was used for all the experiments.

4.1. Dataset

We evaluated our SDSS on two popular semantic segmentation DA benchmarks, GTA5 \(\rightarrow\) Cityscapes and SYNTHIA \(\rightarrow\) Cityscapes, and our new Ocean Ship (synthetic \(\rightarrow\) real).

**Cityscapes.** Cityscapes is a real-world urban scene dataset consisting of 2,975 training, 500 validation, and 1,525 testing images. Following the standard protocols [29, 36], we randomly selected 100, 200, 500, 1,000 and 2,975 images from the training images sequentially for training, and evaluated our SDSS method on the 500 validation images.

**GTA5.** The GTA5 dataset is a synthetic dataset sharing 19 semantic classes with Cityscapes. A total of 24,966 urban scene images were collected from the video game Grand Theft Auto V, and were used as the source domain training data.

**SYNTHIA.** SYNTHIA is a synthetic urban scene dataset. The GTA5 dataset is a synthetic dataset sharing 19 semantic classes with Cityscapes. A total of 24,966 urban scene images were collected from the video game Grand Theft Auto V, and were used as the source domain training data.
dataset. We utilized SYNTHIA-RAND-CITYSCAPES which shares 16 semantic classes with Cityscapes as the source domain dataset. In total, 9,400 images from the SYNTHIA dataset were used as source domain training data.

**Ocean Ship.** Combining large-scale synthetic data with small-scale real-world ones for deep network training is an effective configuration to tackle the lack of large-scale real-world data [26]. Unfortunately, the existing ocean scenario datasets [20, 31] are not large-scale compared to other scenarios [7, 10, 42] relatively. One of the main reasons is the difficulty of real-world data collection. However, large-scale ocean scenario datasets are important because they can be used for various practical applications such as coastal surveillance. Therefore, we have constructed the Ocean Ship dataset consisting of 500 real ocean ship images collected from the Internet and 200K synthetic images with pixel-level annotations created using Unity-based simulation tool. Each part of a ship is categorized into 9 classes: {sea, sky, hull, house, gun, radar, missile, CIWS, and funnel}. Fig. 3 shows the sample images and class distribution of the Ocean Ship dataset. Our dataset provides images with various viewpoints and weather changes similar to those of existing datasets [5, 25, 28].

### 4.2. Implementation details

Following previous works [18, 44, 46], we adopted Deeplab-v2 [2] with the pre-trained ResNet101 [8] on ImageNet [6] as our network architecture. We also followed the training configuration for a fair comparison. Accordingly, we set the batch size to 1, learning rate to $2.5 \times 10^{-4}$, and the number of iteration to 250,000 and early stopped at 120,000 iterations. To verify the effectiveness of our SDSS, we trained the network with a small number of labelled target domain data $D_T$ and source domain data $D_S$ as Baseline. Then, the network was trained with $D_T$ and the subsampled source domain data $D_C$. To verify the sampling effect in a fair manner, the target knowledge network used for source domain data sampling is not used for the subsequent training steps.

### 4.3. Quantitative evaluation on semantic segmentation datasets

In this section, we compare the performance of our SDSS method with state-of-the-art UDA and SSDA methods on public benchmark datasets. In addition, we verify the effectiveness of the SDSS on our new Ocean Ship dataset.

**GTa5 to Cityscapes.** Table 1(a) shows the performance comparison of UDA, fully-supervised, and SSDA methods in the GTa5 to Cityscapes scenario. UDA methods [14, 34, 35, 40] show promising results with only tens of thousands of source domain data without any target domain data. However, if a few labelled target domain data are available, then the fully-supervised method shows a much better performance.

In SSDA, if the source and target domain data are directly combined for the training, then it is helpful only when the target domain labelled data are lacking. By contrast, it becomes harmful when large-scale target domain GT is available. However, with our source domain subsampling method, performance improvement is consistently ensured with additional source domain data regardless of the number of the available target domain data. The proposed method (i.e., SSDA Baseline + Ours) always outperforms the fully-supervised model (i.e., Supervised Deeplab-v2). Furthermore, our method can be seamlessly combined with existing SSDA methods [29, 36] for further performance improvement. We conclude that the role of the proposed SDSS is complementary to the existing SSDA methods.

**SYNTHIA to Cityscapes.** Similar to the GTa5 → Cityscapes scenario, our SDSS method shows consistent performance improvement in the SYNTHIA → Cityscapes scenario as shown in Table 1(b). These results demonstrate the generalization capability of the proposed SDSS method across various synthetic datasets.

### Table 1. Quantitative evaluation results on (a) GTa5 → Cityscapes (19 classes) and (b) SYNTHIA → Cityscapes (13 classes) scenarios. Each method is evaluated on the Cityscapes validation set.

| Type | Method | (a) GTa5 → Cityscapes | (b) SYNTHIA → Cityscapes |
|------|--------|-----------------------|-------------------------|
|      |        | 0 100 200 500 1,000 2,975 | 0 100 200 500 1,000 2,975 |
|      |        | Number of labelled targets | Number of labelled targets |
|      |        | 48.5 - - - - - | 50.37(+4.27) |
|      |        | 45.5 - - - - - | 52.4 - - - - - |
|      |        | 48.5 - - - - - | 54.08(+2.66) |
|      |        | 49.2 - - - - - | - 55.35 56.84 60.96 63.22 67.80 |
|      |        | - 57.82 59.22 61.74 63.80 68.65 | - 58.04 61.96 65.70 67.36 69.90 |
|      |        | - 61.74 63.80 68.65 72.40 75.77 | - 64.20(+2.46) |
|      |        | - 66.44(+2.56) | - 68.40(+1.04) |
|      |        | - 77.54(+1.77) | - 78.91(+1.01) |
|      |        | - 75.77 | - 70.04(+2.24) |
| Supervised | Deeplab-v2 | 41.70 48.16 53.29 57.50 63.03 | 54.56 58.27 62.39 65.64 69.86 |
|      | Baseline | 46.10 52.97 53.52 55.97 59.78 | 55.35 56.94 60.96 63.22 67.80 |
|      | Baseline + Ours | 50.37(+4.27) 51.57(+1.28) 55.62(+2.18) 58.53(+2.56) 63.48(+2.38) | 57.82(+2.45) 60.42(+3.58) 63.19(+2.24) 65.78(+2.56) 70.04(+2.24) |
|      | MME [29] | 51.42 53.46 56.70 60.57 63.11 | 58.04 61.96 65.70 67.36 69.90 |
|      | SSDA MME + Ours | 54.08(+2.66) 55.16(+2.70) 58.61(+1.91) 62.17(+1.69) 64.89(+1.77) | 59.22(+1.18) 63.43(+1.67) 67.27(+1.57) 68.40(+1.04) 70.91(+1.01) |
|      | ASS [36] | 48.5 | 53.15 55.21 60.08 63.12 68.64 | 61.74 63.80 68.65 72.40 75.77 |
|      | ASS + Ours | 56.14(+2.99) 58.42(+3.21) 62.84(+2.76) 65.68(+2.56) 69.65(+1.01) | 64.20(+2.46) 66.44(+2.64) 69.91(+1.26) 73.53(+1.11) 77.54(+1.77) |

Number of labelled sources(Ours) | 17,481 16,622 19,695 20,039 20,764 | 17,481 16,622 19,695 20,039 20,764

*Table 1. Quantitative evaluation results on (a) GTa5 → Cityscapes (19 classes) and (b) SYNTHIA → Cityscapes (13 classes) scenarios. Each method is evaluated on the Cityscapes validation set.*
Ocean Ship (synthetic to real). Our Ocean Ship dataset provides large-scale source domain images, and the difference in the number of images between the source and target domains is large. However, generating several source data and using the entire set for training is inefficient (i.e., the more training data, the longer the training time). Therefore, we applied the SDSS method to our Ocean Ship dataset to efficiently utilize synthetic data and to reduce the computational cost. Table 2 shows the experimental results on our new Ocean Ship dataset. Our method achieved a performance improvement of up to 9.13 mIoU, despite the reduced amount of training data compared to the baseline. Fig. 5 shows the mIoU-Iteration analysis. Deep networks with SDSS achieves higher performance with fewer samples and less training time. These results indicate that the SDSS method works better in real-world scenarios where synthetic data can be generated indefinitely.

Fig. 4 shows the qualitative segmentation performance comparisons between baseline and our methods with 100 and 500 available target GT labels. Our method consistently outperforms the baseline without SDSS, although the number of available target domain data is the same. In addition, performance is further improved with the increased number of available target data (cf. Fig. 4 (a) and (b)). Similar results are obtained with our Ocean Ship dataset as shown in Fig. 4 (c).

Table 2. Quantitative results on Ocean Ship (synthetic → real).

| Type          | Method   | Number of labelled targets |
|---------------|----------|---------------------------|
| Supervised    | Deeplab-v2 | 33.10 37.46 43.88          |
| SSDA          | Baseline  | 35.67 40.72 42.12          |
| SSDA          | Baseline + Ours | 40.30(+4.63) 45.63(+4.91) 51.25(+9.13) |
| Number of labelled sources (Ours) | 41,140 36,574 48,802 |

Figure 4. Semantic segmentation result comparisons between baseline and our methods on various datasets.

4.4. Ablation studies

To further validate the proposed SDSS, we presented ablation studies on the effects of the pixel-level sampling, image-level sampling, and class balancing with detailed analyses. The GTA5 → Cityscapes dataset was used for the experiments.

Effect of pixel-level sampling. To verify the effect of the pixel-level sampling, we compared segmentation performances on the target domain of the models trained with and without pixel-level sampling. We randomly selected 500 images from the target domain training set to pre-train the network that will be used for the sampling on the source dataset. Then, we randomly selected various source domain images to train the segmentation network with and without pixel-level sampling. Note that only source domain sampled data were used for the training in this experiment. Table 3 (a) shows the performance comparison results. With exactly the same subsets of source domain images, models trained with our pixel-level sampling (i.e., $y^c$) showed a significant performance improvement up to 9.09 mIoU over models trained with raw GT labels without sampling (i.e., $y^s$). We also trained the model with labels excluded by the pixel-level sampling (i.e., $y^s \setminus y^c$), and it showed a substantial performance degradation. These results indicate that
In our experiments, properly setting the threshold is important for improving performance in the target domain. In particular, performance improvement is significant for the classes typically occupying small areas in an image such as motorcycles, bicycles, buses, riders, and terrain. Therefore, our SDSS with class balance consideration is effective in improving segmentation performance for minor classes in datasets.

### 5. Discussion & future work

In this study, we investigated a method to efficiently improve the performance of domain adaptation by sampling source data for semantic segmentation. Our motivation can be applied in domain adaptation of various tasks other than semantic segmentation. However, pixel-level sampling is dependent on semantic segmentation. Therefore, to apply our method to object detection, we adopt instance-level sampling, which applies bounding box-level sampling within a single image, instead of pixel-level sampling, which depends on semantic segmentation. For example, if the target knowledge network correctly predicts $c$ out of $t$ GT bounding boxes and classes in an image, then the supervision of $t - c$ bounding boxes would not be used for the training.

The results presented in Table 5 indicate that using source domain data sampling is also effective for domain adaptation in object detection. The network used in the experiment and all hyperparameters follow [24]. How-
ever, because our experimental results involve simply replacing pixel-level sampling with instance-level sampling rather than applying or optimizing all our sampling methods, we intend to further investigate how to efficiently apply other tasks in future work.

6. Conclusion

In this paper, we proposed source domain subset sampling (SDSS) method for semi-supervised domain adaptation. Our method effectively subsamples source domain data with the proposed pixel-level and image-level sampling strategies based on the knowledge learned from a small amount of available target domain labelled data. To verify the effectiveness of our method, we further have constructed a new dataset called Ocean Ship containing 500 real and 200K synthetic images with GT labels. Experimental results on two public datasets and our dataset demonstrate that our method has brought significant segmentation performance improvement with a reduced number of source domain data in a shorter training time.

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