LEVERAGING SCALE-INVARIANCE AND UNCERTAINTY WITH SELF-SUPERVISED DOMAIN ADAPTATION FOR SEMANTIC SEGMENTATION OF FOGGY SCENES

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ABSTRACT:

This paper presents FogAdapt, a novel approach for domain adaptation of semantic segmentation for dense foggy scenes. Although significant research has been directed to reduce the domain shift in semantic segmentation, adaptation to scenes with adverse weather conditions remains an open question. Large variations in the visibility of the scene due to weather conditions, such as fog, smog, and haze, exacerbate the domain shift, thus making unsupervised adaptation in such scenarios challenging. We propose a self-entropy and multi-scale information augmented self-supervised domain adaptation method (FogAdapt) to minimize the domain shift in foggy scenes segmentation. Supported by the empirical evidence that an increase in fog density results in high self-entropy for segmentation probabilities, we introduce a self-entropy based loss function to guide the adaptation method. Furthermore, inferences obtained at different image scales are combined and weighted by the uncertainty to generate scale-invariant pseudo-labels for the target domain. These scale-invariant pseudo-labels are robust to visibility and scale variations. We evaluate the proposed model on real clear-weather scenes to real foggy scenes adaptation and synthetic non-foggy images to real foggy scenes adaptation scenarios. Our experiments demonstrate that FogAdapt significantly outperforms the current state-of-the-art in semantic segmentation of foggy images. Specifically, by considering the standard settings compared to state-of-the-art (SOTA) methods, FogAdapt gains 3.8% on Foggy Zurich, 6.0% on Foggy Driving-dense, and 3.6% on Foggy Driving in mIoU when adapted from Cityscapes to Foggy Zurich.

1. INTRODUCTION

Semantic segmentation is one of the important components of autonomous systems, i.e., self-driving cars [Geiger et al., 2012]. Deep Learning approaches for semantic segmentation, relying on the large tagged datasets [Cordts et al., 2016, Ros et al., 2016], have resulted in substantially improved performance [Sakaridis et al., 2018a, Zhao et al., 2017, Chen et al., 2018a] in the last few years. However, similar to many other supervised learning problems [Khodabandeh et al., 2019, Marsde et al., 2018], semantic segmentation models exhibit large generalization errors [Zou et al., 2018, Vu et al., 2019a, Sahambi and Ali, 2020]. This behavior is ascribed to the domain shift between the distribution of the test and training data domains [Zhang et al., 2017, Lian et al., 2019]. One of the challenging case of the domain adaptation could be attributed to weather conditions such as rain, fog, snowfall, lightning and strong wind [Chen et al., 2019, Sakaridis et al., 2018a, Vachmanus et al., 2020]. Fog specifically degrades the visibility and contrast significantly [Narasimhan and Nayar, 2003, Tan, 2008], deteriorating the performance of the computer vision applications, e.g., segmentation. Domain adaptation algorithms have been presented to overcome the domain shift (synthetic to real [Tsai et al., 2018, Zou et al., 2018, Iqbal and Ali, 2020] or real to real [Chen et al., 2017] datasets) specific to the case of semantic segmentation. However, very little attention has been devoted to address domain shift caused by foggy weather conditions [Sakaridis et al., 2018b, Sakaridis et al., 2018a, Dai et al., 2019].

In this work, we present a novel self-supervised domain adaptation method, FogAdapt, for semantic segmentation of images captured in dense foggy weather. In foggy conditions, the image contrast and color quality drop significantly degrading the clarity and visibility of the scene. This occurs due to the presence of particles in the atmosphere which scatter and absorb light [Tan, 2008, Narasimhan and Nayar, 2003]. Since these particles might be non-uniformly present in different parts of the scene, fog could eventually be of different densities at different locations. Similarly, depending upon the distance between the camera and the objects, fog affects the visibility of objects differently. Specifically, the visibility is decreased with increasing distance, e.g., the farthest objects are more difficult to recognize. An illustration is shown in Fig. 1, where keeping everything else constant, as the fog density is varied from clear to dense, the corresponding semantic segmentation deteriorates accordingly, with the farthest regions most affected. Combination of these variations results in a considerably large set of scenarios, making collection and labeling costly and laborious, especially for the semantic segmentation and robust supervised learning techniques. Hence, need for a robust unsupervised domain adaptation (UDA) method for such a challenging scenario of dense fog in the target images.

To counter the challenges posed by domain shift in dense foggy scenes, we present a novel self-supervised domain adaptation method (FogAdapt) for UDA of foggy scenes segmentation. Our domain (fog) specific empirical analysis led us to discover relationships between the effect of fog and road-scene segmentation. We exploit the relationship between uncertainty, measured by self-entropy, and the density of fog (Fig. 2) by defining a self-entropy minimization loss for the target images, when a source (clear weather images) trained semantic segmentation model is utilized for the target (foggy image) dataset. Similarly, we explore the image scale and fog relationship (Fig. 3) and generate pseudo-labels at pixel level by exploiting the consistency constraint over image scaling to counter the effect of fog. Below we discuss in detail the empirical analysis and the proposed solution specifically designed to counter the effects of fog with further details in Section 3..

Self Entropy loss & Fog Density: Images taken in fog exhibit degradation of color quality, low contrast, and other artifacts associated with low visibility. Overall this results in images with texture, edges, and color information deteriorated enough to make it difficult to differentiate between different objects and
stiff classes. This loss of information results in a confusing semantic segmentation network (trained in normal weather), making it unable to differentiate between different category pixels, resulting in high self-entropy. This relationship between the self-entropy and the density of the fog has been presented in Fig. 2.

To observe how the self-entropy changes with respect to the fog-density, we use Foggy-Cityscapes, a simulated fog added real imagery dataset [Sakaridis et al., 2018a], where the same images and their foggy versions at multiple visibility ranges are available. We manually choose and extract small patches (100 × 150 pixels) from the same locations of the normal images and their modified versions with simulated dense and moderate fog added to it. Self-entropy maps are computed for each patch after passing these images through semantic segmentation network, trained on GTA non-foggy images. Few of them are shown in Fig. 2. The three distributions obtained for all the extracted patches at respective fog levels (Fig. 2 (a)) visualized in Fig. 2 (b), indicate a strong relationship between fog density and self-entropy, i.e., the denser the fog, the higher the self-entropy. This lead us to our hypothesis that minimizing the self-entropy may force the network to learn to compensate for the information loss occurring due to the fog.

Scale Invariance & Fog Density : Previously, LSE [Subhani and Ali, 2020] introduced scale-invariant examples in the target dataset to minimize the inconsistency between normal and larger scales. More specifically, they observed that in clear weather conditions, images at normal scale are segmented well instead of larger scale and hence they generated pseudo-labels at normal scale. However, in dense foggy scenes, this hypothesis is not completely true. In foggy scenes, resizing results in different segmentation accuracy at different locations of the input image depending upon the density of fog and how far or near the object is from the camera. This is especially true for the road scenes. Due to fog, the objects that are far from the camera (and hence smaller in scale) have lower visibility, Eq.(1) making it further challenging to segment it correctly. Since we are employing a self-supervised training approach, pseudo-labels for the small and far away objects disposed in fog will not be available as they will have low segmentation scores. Therefore, we propose a scale-invariant pseudo-labels generation process for foggy scenes adaptation by exploiting the relationship between scale, fog, and self-entropy (Fig. 3). We make a reasonable assumption that pseudo-labels should be scale-invariant. Using the same source trained model, the input target image is segmented at multiple image scales (higher and lower spatial resolution than original) independently and the output probability volume is aggregated. Segmenting at large scale extrapolates the local context and hence produces better segmentation and low entropy for faraway dense foggy regions compared to normal scale. Similarly, segmenting at small scale benefits large and near to camera objects disguised by fog as shown in Fig. 3. The combined effect of these three scales produces better pseudo-labels compared to single normal scale as shown later in Table. 6.

To summarize, this work produces the following contributions.

1. A self-supervised domain adaptation strategy for foggy scenes segmentation with pixel-level pseudo-labels to adapt the output space.
2. Exploiting relationship between the image scale and fog-density to design a strategy for generating scale invariant pixel-wise pseudo-labels.
3. Based on empirical evidence, defining a relation between fog density and self-entropy, i.e., self-entropy minimization loss to mitigate the effects of dense fog in segmentation model and produce confident segmentation output.
4. State-of-the-art (SOTA) performances on benchmark datasets by augmenting the scale invariance and self-entropy with spatial distribution priors of the source dataset.

The rest of the paper is arranged as follows: Section 2. describes related work. Section 3. details the proposed approach and Section 4. presents the experiments and results. In Section 5. we summarize our work for the conclusion.

2. RELATED WORK

Domain adaptation approaches have been presented to overcome the domain shift specific to the case of semantic segmentation [Tsai et al., 2018, Zou et al., 2018, Vu et al., 2019a, Iqbal and Ali, 2020a]. However, very little attention has been devoted to address domain shift caused by foggy weather conditions [Sakaridis et al., 2018b, Sakaridis et al., 2018a, Dai et al., 2019]. Below, we
2.1 Domain Adaptation for Semantic Segmentation

Adversarial learning based UDA of semantic segmentation is the most explored approach in literature [Kim and Byun, 2020; Zhang et al., 2018a; Kim et al., 2019; Gong et al., 2019; Chen et al., 2018b]. In UDA, adversarial loss-based training is leveraged for input space adaptation (re-weighting) [Zhang et al., 2018b; Hoffman et al., 2018], feature matching [Iqbal and Ali, 2020b; Chang et al., 2019; Chen et al., 2019, 2017; Mancini et al., 2018; Sankaranarayanan et al., 2018], structured output matching [Tsi et al., 2018, 2019a; Kim et al., 2019] or combination of these strategies [Kim et al., 2019; Vu et al., 2019b; Zhang et al., 2018a].

However, due to the global nature of adversarial learning even if the objective is to match the output probabilities or the high dimensional feature representation at latent space, the adversarial domain adaptation alone produces sub-optimal results [Vu et al., 2019a; Kim et al., 2019, Iqbal and Ali, 2020b].

Besides adversarial learning, self-supervised domain adaptation is gaining attention for many computer vision applications [Zou et al., 2018a, Iqbal and Ali, 2020b; Khodabandeh et al., 2019]. The authors in [Zou et al., 2018a; Zou et al., 2019] presented a class balanced pseudo-labels generation and confidence regularized self-training with class spatial priors. The authors in MLSL [Iqbal and Ali, 2020a] leveraged spatial invariance to generate consistent pseudo-labels at pixels and image level for UDA of semantic segmentation in clear-weather scenes. LSE [Subhani and Ali, 2020] tried to generate scale-invariant examples and minimized the loss between pseudo-labels generated at normal scale and its zoomed version. Compared to proposed FogAdapt, the LSE [Subhani and Ali, 2020] and MLSL [Iqbal and Ali, 2020b] do not exploit multi-scale information during pseudo-label generation, hence producing inferior performance when exploited to foggy scenes. Zhang et al. [Zhang et al., 2019] proposed a curriculum domain adaptation by defining land-mark super-pixels classification based loss at the output while addressing the easy examples first. PyCDA [Lian et al., 2019] combined [Zou et al., 2018a] and [Zhang et al., 2019] in a single framework to generate pseudo-labels at multiple sized windows. The authors in [Vu et al., 2019a] used a direct entropy minimization (only high entropy pixels) approach along with the adversarial learning applied on the self-entropy maps of the semantic segmentation.

2.2 Domain Adaptation for Foggy Scenes Segmentation

2.2.1 Image Defogging/Dehazing Color quality and contrast of the outdoor scenes are degraded due to the fog/haze. There have been many classical [He et al., 2010; Kim et al., 2011; Kim et al., 2013; Ancuti and Ancuti, 2014] and deep learning [Chen et al., 2019; Morales et al., 2019; Golts et al., 2019; Du and Li, 2018; Kim et al., 2019; Liu et al., 2019] based methods trying to improve color quality or contrast enhancement with an attempt to defog or dehaze. However, as the fog density increases, the defogging models’ performance is degraded significantly. Therefore, attempt to use them as pre-processing step before feeding to computer vision models created/trained in normal light settings does not provide desired performance enhancement [Pei et al., 2018].

2.2.2 Foggy Scenes Segmentation and Adaptation Besides the great progress for generic semantic segmentation and domain adaptation, very little attention is being devoted to handle foggy scenes. This is mainly due to the unavailability of annotated datasets for foggy scene segmentation. The authors in [Sakaridis et al., 2018a] leveraged the stereo property of Cityscapes images to estimate the depth and proposed a fog simulation method for real imagery. They tried to add synthetic fog to real Cityscapes.
images at multiple fog density levels defined by Eq. 2 to generate synthetic fog added real images with multiple visibility ranges (Fig. 1). Alongside, they also developed a small annotated dataset having real foggy scenes; Foggy Driving. Further, they fine-tuned the normal Cityscapes trained model on Foggy-Cityscapes images to address foggy scenes in real imagery. Similarly, the authors in [Hahner et al., 2019] tried to address the real foggy scenes segmentation problem with the help of purely synthetic foggy data. They fine-tuned the normal cityscapes trained models on the synthetic foggy images. Sakaridis et al. [Sakaridis et al., 2018b, Dai et al., 2019] proposed a curriculum adaptation learning approach for real foggy scenes understanding. They developed a large dataset, Foggy Zurich, by capturing road driving scenes under real foggy scenarios. The dataset is unlabeled except a small chunk of 40 images that have dense annotations available. They adapted to Foggy Zurich alongside the fully labeled Foggy-Cityscapes images. They generated pseudo-labels for target images using [Sakaridis et al., 2018a] and defined a fog estimator for curriculum learning. However, they did not investigate the effect of fog and induced uncertainty due to fog during adaptation.

In summary, the existing solutions for foggy scenes adaptation have multiple shortcomings. The generic adaptation methods fail to perform in foggy conditions due to lack of domain knowledge. The fog-specific approaches proposed in [Sakaridis et al., 2018a, Hahner et al., 2019, Sakaridis et al., 2018b, Dai et al., 2019] do not specifically investigate the effect of fog density and respective induced uncertainty. Besides, we introduce a self-supervised domain adaptation approach for foggy scenes by exploiting the relationships between fog density and uncertainty and scale invariance.

3. APPROACH

In this section, we present the details of the proposed approach for self-supervised domain adaptation of semantic segmentation model for dense foggy scenes. We start with an introduction to the optical model for fog, basic architecture for semantic segmentation [Wu et al., 2019] and self-training method for domain adaptation [Zou et al., 2018, Iqbal and Ali, 2020a]. Next, we present the proposed FogAdapt algorithm including the loss functions.

3.1 Optical Model for Fog

In general, the image fogging/hazing process is often represented as the physical corruption model given by Eq. 1 [Sakaridis et al., 2018a]

\[ I_d(r, c) = J(r, c) \cdot t(r, c) + A(1 - t(r, c)), \]

(1)

where \( I_d \) is degraded image, \( t \) is the transmittance map, \( J \) is the fog-free radiance of the original image and \( A \) represents the global atmospheric lighting \( (r, c) \) in Fig. 1 shows the pixel locations). The transmittance map \( t \) is dependent on the distance \( l(r, c) \) of the observer from the object having a homogeneous medium and is given by Eq. 2,

\[ t(r, c) = \exp(-\beta l(r, c)). \]

(2)

The parameter \( \beta \) is used to control the density of fog as leveraged by [Sakaridis et al., 2018a]. Compared to daylight imagery with clear weather conditions, the foggy scenes are more challenging. As highlighted earlier, extensive research has been done on image defogging/dehazing, while less attention is being paid to foggy scenes segmentation and adaptation.

3.2 Self-Supervised Domain Adaptation: Preliminaries

Let \( X_s \subset \mathbb{R}^{H_s \times W_s \times 3} \) and \( X_t \subset \mathbb{R}^{H_t \times W_t \times 3} \) be source domain (clear weather) and target domain (foggy) RGB images with spatial resolution \( H_s \times W_s \) and \( H_t \times W_t \) respectively. The true segmentation labels for source domain images are denoted by \( y_s \subset \mathbb{R}^{H_s \times W_s \times C} \) (each pixel location is one-hot encoded) while the ground truth labels for target images are not available. \( C \) is total number of classes. Let \( \mathcal{J} \) be the fully convolutional semantic segmentation model, with trainable parameters \( \theta \). For a given source image \( x_s \in X_s \), let the output segmentation probability volume be denoted by \( P_s(x_s) \). For source domain images, the segmentation model is trained using the cross entropy loss defined in Eq. 3,

\[ \mathcal{L}(x_s, y_s) = - \sum_{h_s \in H_s} \sum_{w_s \in W_s} \sum_{c \in C} y_s(h_s, w_s, c) \log(P_s(h_s, w_s, c)) \]

(3)

where \( y_s \in Y_s \) shows the corresponding ground-truth segmentation labels. Since the true labels for target domain images are not present, we use pseudo-labels generated by the source domain trained model for fine-tuning (adaptation). The corresponding cross entropy loss for the target images is defined in Eq. 4,

\[ \hat{\mathcal{L}}(x_t, \hat{y}_t) = - \sum_{h_t \in H_t} \sum_{w_t \in W_t} \sum_{c \in C} \rho(h_t, w_t) \hat{y}_t(h_t, w_t, c) \log(P_s(h_t, w_t, c)) \]

(4)

where \( \hat{\mathcal{L}}(x_t, \hat{y}_t) \) is self-supervised training loss for target domain images with pseudo-labels \( \hat{y}_t \). The \( \rho(h_t, w_t) \) is a binary map used to compute and backpropagate loss for only those pixels which are assigned pseudo-labels and ignore otherwise. More specifically, for any pixel location, \( \rho(h_t, w_t) = 1 \) if that pixel is assigned a pseudo-label and \( \rho(h_t, w_t) = 0 \) otherwise. The pseudo-labels generation and training processes for FogAdapt are shown in Fig. 4 (Sec. 3.3). During target adaptation, the segmentation network is jointly trained using the generated pseudo-labels of the target images and the ground truth labels of source images. The corresponding joint loss function for self-supervised domain adaptation (SSDA) is given by

\[ \min_0 L_{SSDA}(x_s, y_s, x_t, \hat{y}_t) = \mathcal{L}(x_s, y_s) + \hat{\mathcal{L}}(x_t, \hat{y}_t) \]

(5)

The \( L_{SSDA} \) in Eq. 5 is minimized following a sequential scheme, i.e., fix the segmentation model weight \( \theta \) to generate pseudo-labels \( \hat{y}_t \) for target samples \( x_t \), and then use these pseudo-labels to minimize Eq. 5 with respect to \( \theta \). These steps are repeated for multiple iterations called rounds. The pseudo-labels generation exploiting scale invariance and other constraints are discussed below.

3.3 Scale Invariant Pseudo-Labels

To adapt the target domain effectively, accurate pseudo-labels are required. However, in dense foggy scenes, it is very difficult to generate accurate and consistent pseudo-labels. As described in Fig. 3 and explained in Section 1., under dense foggy conditions, image regions behave differently at multiple scales. Hence, combining multi-scale output information intelligently (Fig. 4(a)) is more effective compared to any single scale (Table. 6). Therefore, we present scale-invariant pseudo-labels created by weighted summation of the probability and uncertainty maps across different image scales.

As discussed in Section 1. and shown in Fig. 1, in foggy scenes the visibility of the object is correlated with density of fog.
Figure 4: The proposed FogAdapt framework. (a) Scale-invariant pseudo-labels generation process where, 1) a target image is resized at multiple scales. 2) the resized versions of the image are segmented independently, 3) uncertainty (self-entropy) based weight maps for each image scale are defined and the outputs are weighted respectively 4) the weighted outputs are then resized to the original scale and recombined, and 5) most confident pixels are assigned pseudo-labels. (b) shows the semantic segmentation adaptation using the generated pseudo-labels for target domain images in (a) and the true labels of source domain images simultaneously.

To overcome the limitation of dense fog on far away objects and to overcome the problems associated with the fixed receptive field being unable to provide the complete coverage to larger and near to camera objects, we generate scale-invariant pseudo-labels. Instead of generating pseudo-labels at the original (normal) scale that objects exist in an image, we process target images at multiple scales (spatial resolutions/zoom levels) to generate pseudo-labels, as shown in Fig. 4(a). To assure semantic consistency and scale-invariance, we assume that objects and stuff should be segmented the same irrespective of the scale they are presented. We evaluate the target image at three scales, e.g., $S = \{1 + s_0, 1, 1 - s_0\}$, where $s_0$ is a scale parameter and set to $s_0 = 0.25$ in this work. The target image is resized according to the three scale parameters into three separate images and segmented independently. We combine these probability maps based on the confidence of the segmentation model. Specifically, corresponding to each scale, we generate normalized weight maps ($w_{(1-s_0)}$ and $w_{(1+s_0)}$) based on the self entropy $H(H_t, W)$ (Eq. 8) of the segmentation probabilities corresponding to each scale. This process for $w_{(1-s_0)}$ is shown in Eq. 6.

$$w_{(1-s_0)} = \frac{1 - H(H_t, W_1)(P_{x_{(1-s_0)}})}{\sum_{j \in S} (1 - H(H_t, W_j)(P_{x_j}))}$$  

where $w_j$ with ($j \in S$) are the self-entropy based weight maps for respective scales and the ($\cdot$) operator shows element-wise multiplication. The higher the self-entropy, the lower the contribution in $P_{x_j}$, and vice versa. The $P_{x_j}$ is used to select pseudo-label based on the confidence score. This process of scale-invariant pseudo-label generation is shown in Fig. 4(a). Hence, the generated pseudo-labels are scale-invariant and quantitatively better compared to single inference (Table. 6).

To select pixels with high confidence as pseudo-labels and avoid class distribution imbalance problem, we adopt a class balancing and selecting criteria similar to one used in [Zou et al., 2019]. For each target image, we select the per-pixel high (maximum) probability values from the probability map $P_{x_j}$. These high-probability class values over the whole target set are sorted in descending order of confidence and the pixels with high probabilities are selected as pseudo-labels based on the pre-defined selection portion $s_p$. Initially, $s_p = 15\%$ of the total pixels belonging to any category and is incremented by $5\%$ in each round. The resultant pseudo-labels are class-balanced, consistent, and scale-invariant representative of the whole target dataset.

3.4 Self-Entropy Minimization for Foggy Scenes Adaptation

The density of fog has a direct relation with the information contained in an image, e.g., the denser the fog, the minimum the information. This is evident from the semantic segmentation results, where dense foggy regions in an image have high self-entropy values (Fig. 2). With increasing fog density, the segmentation model generates under-confident per-pixel predictions making the entropies high. We leverage this relationship between fog density and self-entropy and define a self-entropy minimization loss (9) alongside cross-entropy loss (5). The underlying idea for self-entropy minimization is to shift the mean self-entropy of dense foggy scenes towards clear images self-entropy mean, as shown in Fig. 2 (b). The self-entropy $H$ for a target image $x_t$ is given by Eq. 8.

$$H(H_t, W_t)(P_{x_t}) = -\frac{1}{\log(C)} \sum_{c \in C} P_{x_t}(H_t, W_t, c) \log(P_{x_t}(H_t, W_t, c))$$

where $H(H_t, W_t) \in [0, 1]$ is the per-pixel standard entropy defined in [Shannon, 1948]. The loss function based on $H$ for a
target image \( x_t \) is given by Eq. 9,
\[
\hat{L}_{se}(P_{c}) = \frac{1}{H_t \times W_t} \sum_{H_t \times W_t} h(x_t | H_t, W_t)(P_{c}^{H_t, W_t, c})
\]
(9)

During adaptation, we jointly optimize the pseudo-labels based supervised loss \( \hat{L} \) and the unsupervised self-entropy loss \( L_{se} \) for an input target image \( x_t \). There is a strong resemblance in Eq. 4 and Eq. 9, where the former enforces the segmentation model to assign the correct class to an underlined pixel, while the later tries to maximize individual confidence scores.

3.5 Appearance Adaptation

As described in Section 2., many algorithms tried to exploit the self-training process by labeling the most confident predictions as pseudo-labels. However, it is very important for a pseudo-label to be accurate, consistent, and invariant. To generate such confident pseudo-labels the visual appearance of the target and source domain images also play a vital role. For example, a model trained on normal imagery fails to generate accurate pseudo-labels on dense foggy images. Hence, an appearance adaptation step is required to help self-supervised learning paradigms to generate consistent pseudo-labels.

3.5.1 Image Translation Module

In this work, we leveraged the cycle-consistent adversarial learning algorithm (CycleGAN) [Hoffman et al., 2018] to transform the source domain images to the visual appearance of the unlabeled target domain images. This process is named as Image Translation Module (ITM). The transformed images are nearly similar in visual appearance with target domain images and are used in the domain adaptation process. The loss function for the employed CycleGAN is given by Eq. 10,
\[
L_{c-Gan}(x_s, x_t, G_t, G_s, D_t, D_s) = L_{GAN}(G_t, D_t, x_s, x_t) + L_{GAN}(G_s, D_s, x_t, x_s) + L_{cycle}(x_s, G_t(x_s)) + L_{sc}(x_s, G_t(x_s)),
\]
(10)

where \( G_s \) and \( G_t \) represent the generator from target to source and source to target domain respectively. \( D_t \) is the discriminator applied to classify between original target domain images and translated target domain images. \( D_s \) expedites the same loss for the target to source transformation. Similarly, \( L_{cyc} \) and \( L_{sc} \) losses are applied to maintain the cycle and semantic consistency respectively. The optimization program can be defined as a min-max criterion given in Eq. 11.
\[
\min_{G_t,G_s,D_t,D_s} \max_{c} L_{c-Gan}(x_s, x_t, G_t, G_s, D_t, D_s).
\]
(11)

The transformed source images with available ground truth, when used in domain adaptation helps to select better pseudo-labels and eventually improves the adaptation performance.

3.6 Combined Objective Function

The composite loss function for self-supervision based UDA of foggy scene segmentation is the composition of both Eq. 5 and Eq. 9, and is given by,
\[
L_{comp}(x_s, y_s, x_t, y_t, c) = L_{SSDA}(x_s, y_s, x_t, y_t) + \hat{L}_{se}(P_{c})
\]
(12)

Similarly, the combined loss function for ITM augmented with \( L_{comp} \) is the combination of Eq. 10 and Eq. 12 and is given by Eq. 13,
\[
\hat{L}_{ITM-comp} = L_{c-Gan}(x_s, x_t, F_t, P_s, D_t, D_s) + L_{comp}(x_s, y_s, x_t, y_t, c).
\]
(13)

To summarize the proposed approach, we train CycleGAN using Eq. 11 to translate source images to look alike target images. Next, we generate scale-invariant consistent pseudo labels and adapt the baseline model in an iterative manner to minimize the loss function \( L_{comp} \) as defined in Eq. 12.

4. EXPERIMENTS AND RESULTS

This section discusses experimental details and provides the results of our comparison with the state of art techniques. We list down different configurations and their acronyms in Table. 1 for better readability.

Table 1 Different configurations and their acronyms.

| Acronyms                  | Configuration                                      |
|---------------------------|----------------------------------------------------|
| FogAdapt                 | Self-entropy loss + Scale-invariance based pseudo-labels |
| FogAdapt+                | ITM (Image Translation Module) + FogAdapt          |
| SP-FogAdapt+             | Spatial-Priors during pseudo-labels generation + FogAdapt+ |

4.1 Experimental Setup

We have performed multiple experiments with various datasets, weather conditions and settings. The key points are discussed below.

4.1.1 Datasets

We adapt the standard real-to-real and synthetic-to-real setup for UDA of foggy scenes segmentation. We use Cityscapes [Cordts et al., 2016], SYNTHIA [Ros et al., 2016] and, GTA [Richer et al., 2016] datasets as source domain and Foggy Driving [Sakaridis et al., 2018a], Foggy-Cityscapes [Sakaridis et al., 2018b] and foggy zurich [Dai et al., 2019] as real-world target domain datasets. The SYNTHIA-RAND-CITYSCAPES, a sub-set from the SYNTHIA dataset consists of 9400 synthetic frames of spatial resolution 760 × 1280. The baseline models and the adapted models are both evaluated with 16 and 13 categories common between SYNTHIA and Foggy-Cityscapes as described in [Vu et al., 2019a] and [Zou et al., 2018] for normal Cityscapes. Similarly, we use the GTA dataset having 24966 frames with a high spatial resolution of 1052 × 1914. Pixel-level labels for classes compatible with Foggy-Cityscapes are available for all 24966 frames. The Cityscapes dataset consists of 3475 high resolution (1024 × 2048) images with pixel-level annotations, where 2975 images are listed as the training set and the remaining 500 as validation. The Foggy-Cityscapes have the same images as cityscapes with fog being added synthetically by [Sakaridis et al., 2018b]. The Foggy Driving (FD) dataset contains 101 images where 33 images have fine annotations and the remaining have coarse labels available. Foggy Driving Dense FDD is a subset of the FD dataset having 21 images with very dense fog. Similarly, the Foggy Zurich dataset contains 3808 high-resolution images of real foggy scenes. However, only a limited set of 40 images is labeled for semantic segmentation.

4.1.2 Model Architecture

For semantic segmentation of foggy scenes, we use ResNet-38 [Wu et al., 2019] as baseline. The ResNet-38 is trained for segmentation of Cityscapes, SYNTHIA, and GTA datasets using the ImageNet trained parameters [Russakovsky et al., 2015]. The architecture of ResNet-38 for segmentation in this work is the same as defined in [Wu et al., 2019, Zou et al., 2018]. The Image Translation Module (ITM) is adapted from [Hoffman et al., 2018]. The ITM is employed to translate source images to the visual appearance of the target domain datasets, e.g., from GTA to Foggy-Cityscapes.
Table 2 Semantic segmentation performance of FogAdapt and its variants compared to SOTA methods on Foggy Zurich (FZ), Foggy Driving-dense (FDD) and Foggy Driving (FD) test sets when adapted from Cityscapes to FZ. We present mIoU for all classes compatible with Cityscapes [Cordts et al., 2016], and frequent classes defined for FZ, FDD, and FD respectively. FogAdapt+: FogAdapt+CycleGAN, SP-FogAdapt+: FogAdapt+ combined with spatial priors defined in [Zou et al., 2018]. The bold text shows highest whereas the underlined show the second-highest scores.

| Dataset                  | FZ       | FDD     | FD       | FZ       | FDD     | FD       |
|--------------------------|----------|---------|----------|----------|---------|----------|
| AdaptSegNet [Yan et al., 2018] | 25.0     | 18.8    | 29.7     |          |         |          |
| Semantic [Sakaridis et al., 2018a] | -        | 37.8    | -        | -        | 57.4    |          |
| Curriculum-FT [Dai et al., 2019] | 36.7     | -       | -        | 51.7     | -       | -        |
| SUSF [Habner et al., 2019] | 42.7     | 48.6    | 63.0     | 59.5     |         |          |
| Model-Ada [Sakaridis et al., 2018b] | 42.9     | 37.3    | 48.5     | -        | -       | -        |
| MLSL [Iqbal and Ali, 2020a] | 45.5     | 43.3    | 43.5     | 61.0     | 46.5    | 58.8     |
| Curriculum-A [Dai et al., 2019] | 46.8     | 43.0    | 49.8     | -        | -       | -        |
| ResNet-38 (baseline) [Wu et al., 2019] | 33.8     | 39.2    | 39.4     | 48.0     | 43.9    | 56.6     |
| Ours(FogAdapt)           | 48.8     | 46.5    | 52.0     | 64.2     | 51.1    | 63.5     |
| Ours(FogAdapt+)          | 49.8     | 47.1    | 52.4     | 64.4     | 51.6    | 63.7     |
| Ours(SP-FogAdapt+)       | 50.6     | 49.0    | 53.4     | 64.6     | 53.1    | 65.7     |

4.1.3 Implementation and Training Details

To perform the experiments, a core-i5 machine with a single GTX-1080Ti having 11GB of memory is used while MxNet [Chen et al., 2015] is used as deep learning framework. SGD optimizer with an initial learning rate of $1 \times 10^{-4}$ for the segmentation model and $2 \times 10^{-4}$ for ITM respectively are used for training. To enforce scale-invariance, the images are segmented at three scales to generate pseudo-labels, e.g., $S = \{1 + s_c, 1 - s_c\}$, where $s_c$ is a scale parameter and is set to $s_c = 0.25$ in this work. Similarly, $s_v$ is initially set to 15% of the total pixels belonging to any category for pseudo-labels selection and is incremented by 5% in each round (Sec. 3.3). Due to GPU memory limitations, we process two images per mini-batch. The proposed FogAdapt+ iterative process of self-supervised domain adaptation is continued for 4 rounds where each round consists of 2 epochs of training.

4.2 Experimental Results

In this section, we show and discuss the experimental results of the FogAdapt compared to ResNet-38 (baseline) and current state-of-the-art (SOTA)UDA approaches for foggy scenes. Our experiments are two fold: (a) In the first setup, we use normal Cityscapes (clear-weather images) dataset as source domain and Foggy Zurich and Foggy Driving (real-foggy imagery) as target domain datasets and (b) in the second setup, we use synthetic datasets, e.g., SYNTHIA and GTA as source domain and Foggy-Cityscapes (synthetic fog added to real images) dataset as target domain. The performance is reported using a standard evaluation metric for segmentation, i.e., Mean Intersection over Union (mIoU). The proposed FogAdapt performs superior compared to other domain adaptation approaches with SOTA performance on multiple benchmark datasets varying from synthetic to real for dense foggy conditions.

4.2.1 Real Non-foggy to Real-Foggy Scenes Adaptation

Following [Sakaridis et al., 2018b, Dai et al., 2019], we adapt the normal (clear-weather) cityscapes dataset trained source model to real foggy imagery dataset, Foggy Zurich. Alongside Foggy Zurich evaluation set, we also evaluate our baseline and Foggy Zurich (FZ) adapted model over Foggy Driving (FD) and Foggy Driving-dense (FDD) datasets.

Cityscapes $\rightarrow$ Foggy Zurich: Table 2 summarizes the quantitative results of the proposed approach compared to current SOTA methods. The proposed FogAdapt+ outperforms the ResNet-38 (baseline) and existing approaches with a high margin. Compared to ResNet-38 [Wu et al., 2019] baseline, we gain 16.0% in mIoU over all classes. We also evaluate FogAdapt over frequent classes in the FZ dataset, e.g., road, sidewalk, building, wall, fence, pole, traffic-light, traffic-sign, vegetation, sky, and car defined by [Dai et al., 2019]. The FogAdapt+ attains a gain of 22.4% in mIoU over ResNet-38 baseline. Similarly, compared to Curriculum-Ada [Dai et al., 2019] and Model-Ada [Sakaridis et al., 2018b], the proposed FogAdapt+ outperforms with significant margins of about 3.0% and 7.0% over all classes respectively. The addition of spatial priors further improves the results as shown by SP-FogAdapt+ in Table 2. To have a fair qualitative comparison, we selected the same images presented in [Dai et al., 2019] as shown in Fig. 5. The proposed FogAdapt shows a significant performance improvement over baselines and existing SOTA methods in most of the categories.

Evaluation on Foggy Driving: Since the FD dataset is small having 33 images with line (every pixel is assigned a label) dense annotations and the remaining 68 images with coarse (polygon annotations with no clear object boundaries) annotations, this dataset is used only for evaluation as suggested by [Sakaridis et al., 2018a]. We evaluate our baseline and FZ adapted models over FD and its’ subset FDD. The quantitative results for all 19 classes compatible with FZ dataset are shown in Table 2. The proposed FogAdapt+ performs superior compared to baselines and existing SOTA methods. Especially, in case of dense foggy scenes, FDD, our FogAdapt+ achieves a gain of 4.1% and 9.8% in mIoU compared to Curriculum-Ada [Dai et al., 2019] and Model-Ada [Sakaridis et al., 2018b] respectively.

Similar to the FZ dataset, we evaluate the FD dataset for frequent classes, e.g., road, sidewalk, building, pole, traffic-light, traffic-sign, vegetation, sky, person, and car as defined by [Sakaridis et al., 2018a]. The proposed FogAdapt+ performs significantly better in mIoU, i.e., a minimum gain of 5.1% compared to strong MLSL [Iqbal and Ali, 2020a].

4.2.2 Synthetic to Real-Foggy Scenes Adaptation

To comprehensively test the proposed approach, we also perform synthetic to real foggy domain adaptation experiments. Specifically, we use synthetic datasets, e.g., SYNTHIA and GTA as source domain datasets and Foggy-Cityscapes dataset as target domain. The Foggy-Cityscapes dataset has the real Cityscapes images with synthetic fog added as proposed by [Dai et al., 2019]. The Foggy-Cityscapes have three levels of fog, e.g., low fog with 600-m visibility, medium fog with 300-m visibility, and dense fog with 150m visibility (Fig. 1). In this work, we have adapted our models to dense fog scenarios of the Foggy-Cityscapes dataset.

GTA $\rightarrow$ Foggy-Cityscapes: As indicated in Table 3, the proposed FogAdapt+ for self-supervised domain adaptation shows SOTA performance. More specifically, the FogAdapt+ improves the segmentation performance on dense Foggy-Cityscapes by 11.6%, 7.3% and 5.9% compared to ResNet-38 baseline and previous SOTA methods, i.e., CBST [Zou et al., 2018] and MLSL [Iqbal and Ali, 2020a] respectively. Similarly, compared to LSE [Subhani and Ali, 2020] and PyCDA [Lian et al., 2019], the proposed approach outperforms with a minimum margin of 5.0%. Fig. 6 shows semantic segmentation results before and after adaptation. The proposed approach significantly improves the segmentation performance of dense foggy scenes compared to baseline and previous SOTA methods.


As discussed in Sec. 3.3, the higher the fog density, the more uncertain the segmentation model becomes about assigning a class to a specific pixel (Fig. 3). This decrease in information eventually increases the self-entropy of segmentation probabilities (Fig. 2). We leverage this relation between entropy and fog density and add an entropy minimization constraint (Eq. 9) to the total loss function. Adding this constraint increases the mIoU performance compared to simple pseudo-labels based self-supervised domain adaptation (SSDA) further by 3.3% for GTA to Foggy-Cityscapes as shown in Table 5.

Table 5 Effect of self-entropy and scale invariance. SSDA: Self-supervised domain adaptation. Here SE is Self-entropy while SI is Scale Invariance.

4.3.2 Scale-Invariance

As the effect of fog increases with the distance between the object and the observer, the scale of an object has a major role (Fig. 3) in properly segmenting the object. Increasing the object’s size by resizing the image to a larger scale makes the object under fog clearer as it increases the local contextual information (Fig. 3). This helps in generating comparatively better pseudo labels (Table. 6). On the other hand, resizing image to a smaller size allows the segmentation algorithm to propagate information (Fig. 3). This helps in generating comparatively better pseudo labels (Table. 6). On the other hand, resizing image to a smaller size allows the segmentation algorithm to propagate information (Fig. 3) to more global view. As described in Sec. 3.3, combining these higher and lower scales results in the generation of robust and consistent pseudo-labels (Table. 6), which eventually increases the performance over foggy scenes. Experimental results show
Figure 6: Semantic segmentation qualitative results on Foggy-Cityscapes validation set when adapted from GTA dataset trained model. The FogAdapt performs better compared to existing methods. Specifically, the small, thin and far away objects disguised in fog and the stuff classes like road, sidewalk, buildings and sky are segmented better.

Table 2 Segmentation results of adapting SYNTHIA to Foggy-Cityscapes. We present mIoU and mIoU* (13-categories as presented by [Tsai et al., 2018]) on the Foggy-Cityscapes validation set.

Table 6 A comparative analysis of image transformation methods in dense foggy scenes adaptation process.

4.3.3 Effect of Input Space Adaptation With ResNet-38 [Wu et al., 2019] as baseline model, we investigate the effect of image translation at input space. We train CycleGAN [Hoffman et al., 2018] to translate source images (non-foggy) to the visual appearance (foggy) of the target domain images; GTA/SYNTHIA to Foggy-Cityscapes and Cityscapes to Foggy-Cityscapes adaptation (Table. 5). Similarly, for normal Cityscapes to FZ dataset adaptation, the SI performs superior when combined with SE for FZ, FDD, and FD compared to all previous approaches as shown in Table. 2 (FogAdapt+).

Table 6 Effect of incorporating uncertainty weighted scale invariance on the quality of pseudo-labels. Here wSI is Weighted Scale-Invariance.

In this paper, we have proposed a self-supervised domain adaptation strategy with self-entropy and scale-invariance constraints for UDA of foggy scene semantic segmentation. We empirically establish a relationship between the fog density and self-entropy of the source model’s prediction over the foggy images. We exploit this relationship to define a self-entropy minimization objective function to adapt on images where color quality and contrast has been degraded due to fog. Having a fair assumption that under foggy conditions labels of stuff and objects should be the same regardless of their scale, we generate scale-invariant pixel level pseudo-labels. Scale-invariance helps us to counter the phenomena that in foggy weather, objects far away are less visible and hence suffer from more information loss. The scale invariant pseudo-label generation and the self-entropy minimization for self-supervised domain adaptation, allows the segmentation model to learn domain independent features to mitigate the effect of fog density. Rigorous experiments demonstrate that the proposed self-supervised domain adaptation method augmented with image translation module (ITM) outperforms the existing SOTA algorithms on benchmark datasets.

5. CONCLUSION
mIoU improves from 46.8 to 50.6 on Foggy Zurich, 43.0 to 49.0 on Foggy Driving-dense, and 49.8 to 53.4 Foggy Driving when adapted from Cityscapes to Foggy Zurich. Effectiveness of self-entropy minimization, scale invariant pseudo-labels, and ITM is highlighted by the considerable improvement of mIoU over the baseline model and SOTA methods.

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