Automatic Model-Based Dataset Generation for High-Level Vision Tasks of Autonomous Driving in Haze Weather

Meiqi Wang, Tianqi Su, Siyi Chen, Wenhan Yang, Jiaying Liu, Senior Member, IEEE, and Zhongfeng Wang, Fellow, IEEE

Abstract—Improving the performance of high-level computer vision tasks in adverse weather (e.g., haze) is highly critical for autonomous driving safety. However, collecting and annotating training sets for various high-level tasks in haze weather are expensive and time-consuming. To address this issue, we propose a novel haze generation model called HazeGEN by coupling the variational autoencoder and the generative adversarial network to automatically generate annotated datasets. The proposed HazeGEN leverages a shared latent space assumption based on an optimized encoder–decoder architecture, which guarantees high fidelity in the cross-domain image translations. To ensure that the generated image can truly facilitate high-level vision task performance, a semisupervised learning strategy is developed for HazeGEN to efficiently learn the useful knowledge from both the real-world images (with unsupervised losses) and the synthetic images generated following the atmosphere scattering model (with supervised losses). Extensive experiments and ablation studies demonstrate that training the model with our generated haze dataset greatly improves accuracy in high-level tasks such as semantic segmentation and object detection. Furthermore, one important but under-exploited issue is investigated to find out whether the developed dataset can be a good substitute for the real ones. Results show that the generated dataset has the most similar performance to the real-world collected haze dataset on multiple challenging industrial scenarios compared with prior works.

Index Terms—Autonomous driving, haze, object detection, semantic segmentation, semisupervised learning, shared latent space, variational autoencoder–generative adversarial network (VAE–GAN).

I. INTRODUCTION

Deep neural networks (DNNs) have become successful in many computer vision tasks [1], [2], e.g., image recognition, object detection, semantic segmentation, etc. However, when facing adverse weather, such as haze/fog, the captured images lose details and are affected by color casting, which severely degrades the DNN models’ performance on high-level tasks and influences the reliability and efficiency of vision-based systems such as autonomous vehicles (see Fig. 1). Thus, improving the robustness and efficiency of the DNN model in adverse weather attracts significant research attention [3].

One of the solutions to enhance the image quality is to use the preprocessing image enhancement module, such as dehazing module [4]. However, this solution cannot satisfy practical needs due to the lack of consideration of the resource constraint of industrial autopilot systems, which severely slows down the processing process and violates the need for the real-time applications. Furthermore, existing image preprocessing methods might not necessarily be effective for high-level tasks in real-world, because the commonly adopted evaluation metrics (e.g., peak signal-to-noise ratio and structural similarity index) mainly target the signal fidelity between the dehazed images and the corresponding clean ones, which might fail to stand for the performance on high-level tasks [5].

Using a particular annotated dataset to train the model can be a more practicable way for high-level tasks. To obtain the required dataset, some efforts are made to simulate a foggy dataset. Sakaridis et al. [5] and Gao et al. [6] used the atmosphere scattering model [7] to generate a hazy dataset as defined as follows:

\[ I(x) = J(x)t(x) + A(x)(1 - t(x)). \]  

(1)

The hazy image \( I(x) \) is constructed from haze-free image \( J(x) \), transmission map \( t(x) \), and global atmospheric light \( A(x) \). However, the synthetic \( t(x) \) and \( A(x) \) might not be reasonable at the given scenes, which leads to artifacts, such as color casting and noises. Gong et al. [8] tried to learn a direct mapping across

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different domains by using supervised learning with the existing synthetic dataset. However, without the adaption to real hazy images, the output synthetic hazy image has gaps with the real one, leading to high-level tasks’ performance degradation in real scenarios.

In summary, the existing haze dataset generation approaches still have two neglected issues: 1) The majority of prior works rely more on synthetic data and physics model than real haze training images, which makes it challenging to adapt to complex and changing scenarios in real-world industrial environments. 2) Conventional dataset generation approaches might introduce artifacts such as color casting and noises at the same time, which fails to preserve image details and degrades high-level task performance in autonomous driving.

To address the issues mentioned above, multiple innovations are combined together to build an deeply optimized image-to-image translation framework that can truly facilitate the high-level tasks performance improvement. Overall, we propose a haze generation model called HazeGEN trained in a semisupervised way. To directly learn from the real-world haze images that have no paired “ground truth” (i.e., the pixel-to-pixel paired clean images), multiple unsupervised-based losses are developed to leverage the knowledge from the real haze distribution. To better preserve the details of the original clean images, several supervised training losses are also leveraged based on the paired training images synthesized following the atmosphere scattering model [see (1)]. To jointly learn from both unpaired and paired images, we enforce the constraint that the two kinds of images share the same latent space so that the images from the clean, real haze, and synthetic haze domains can be mapped into the same latent code and transferred flexibly. Based on this assumption, we introduce the VAE [9] as the image generator, the effectiveness of which is further enhanced by the adversarial training in GAN to avoid the high-level task performance degradation caused by the low-resolution images generated by VAE-only [10]. With all these components, we generate our photo-realistic haze dataset for high-level task training.

In conclusion, our contributions are highlighted as follows.

1) One end-to-end haze generation model is developed, which can automatically generates haze dataset that can be used to truly boost the high-level task performance. It is noted that the laborious dataset creation process for industrial applications can be eliminated in a more practical way in this work by: 1) demonstrating the superiority of the proposed HazeGEN over not only the previous synthetic haze datasets, but also the prior dehazing works and the real-world collected datasets; 2) measuring the similarity between our generated images and the real-world annotated haze images directly on the the high-level tasks in haze weather, rather than at the pixel level or visual level as in prior works.

2) We are the first to integrate the shared latent space based VAE-GAN into the semisupervised learning to generate haze datasets. The proposed optimizations at the architecture and algorithm levels enable highly effective learning from both real hazy images and prior knowledge for haze modeling with few artifacts, which truly improve the high-level task performance in haze weather.

3) The proposed model is extensively evaluated on two most common tasks (object detection and semantic segmentation) in multiple challenging industrial scenarios, e.g., the real-world haze with diverse distributions (including both the light and dense haze) and the haze-like weather (including dark snow dust and heavy snow). Results show that the performance is increased by as high as 10.03% and 5.93% for object detection and semantic segmentation, respectively. The proposed method greatly surpasses the state-of-the-art (SOTA) hazy generation methods in accuracy, and outperforms the SOTA dehazing methods in both speed and accuracy. These results demonstrate its superiority in supporting the real-time and safety requirements of autonomous driving under various weather conditions.

II. RELATED WORK

A. Dataset Generation Methods in Haze Weather

Many works are proposed to synthesize datasets for haze weather. Zoph et al. [11] used a data augmentation method to generate annotated datasets. However, the method ignores the difference between the style transformation and the mapping from the 3-D physical world into the 2-D image domain. Li et al. [12] used the atmosphere scattering model. However, it introduces artificial flaws and color distortion due to the unavoidable measurement error. The defects lead to a degradation of the performance on high-level vision tasks. Li et al. [13] proposed an end-to-end learned model-based simulation method based on the generative adversarial networks (GAN). However, the GAN models cannot estimate the posterior and are unstable to train. Another method called Cycle-GAN [14] is proposed by utilizing unpaired training data in real-haze and clean days. But without a supervised training constraint, this method leads to an undesired conversion style (e.g., the loss of important details) [15].

B. High-Level Vision Tasks in Adverse Weather

High accuracy of high-level vision tasks such as object detection and segmentation are highly important for safe autonomous
driving. However, most existing works focus on improving their performance in clear days and only recent works explore adverse conditions. Qin et al. [16] applied a preprocessing dehazing model. However, they only paid attention to enhancing the image quality rather than the high-level tasks’ performance. Vishwanath et al. [17] proposed an unsupervised physical-model-based detection framework in hazy and rainy conditions. However, inevitable measuring error in the physical model makes synthesized images include undesirable artifacts, affecting the high-level tasks’ performance. Chen et al. [18] assumed that the adversarial weather conditions result in the domain shift, and they propose a domain adaptive Faster-RCNN to tackle the domain shift problem. However, the synthetic dataset used in the method exhibits a clear difference in appearance with real-world images, which harms object detection performance in the real scene. To conclude, previous attempts are still far from the goal to generating natural hazy images that can benefit high-level vision tasks.

C. Shared Latent Space

The basic assumption behind the image translations between two domains is that some latent factors, such as the high-level embedding features [19], [20], are shared by the source domain and the target domain. Li et al. [21] indicated that a shared manifold for observations can be learnt based on the Gaussian process latent variable model. Furthermore, [22] and [23] used the shared latent space assumption for handwritten pattern recognition and face aging tasks, demonstrating this assumption’s generalizability. Inspired by these works, we propose the HazeGEN framework based on the shared latent space assumption, to map images from clean, synthetic, and real haze domains to the same latent space and recover images from this space.

III. METHOD

In this section, the model architecture of the proposed HazeGEN is introduced first, followed by the loss functions for the semisupervised training to show how the information in real haze scenarios is learnt and how the artifacts are suppressed to ensure the high performance of high-level tasks.

A. Model Structure

When approaching the image translation problem from the probabilistic modeling view, the major difficulty is learning a joint distribution from the marginal distributions in two different domains since there exist an infinite number of joint distributions that can lead to the specified marginal distributions [24]. To address this ill-posed issue, we need to make an additional assumption about the joint distribution.

Inspired by the works [21], [22], [23], we make the shared-latent space assumption. In the assumed space, there exists a shared latent code for any given pair of images \( x_1 \) and \( x_2 \). This code allows us to recover both images from it. Following the shared-latent space assumption, we build the domain transformations in this work as illustrated in Fig. 2.

Specifically, the generator (\( GEN \)) of VAE and the discriminator (\( DIS \)) from GAN are combined to build the image translation framework as shown in Fig. 3. In each \( GEN \), an encoder–decoder (E–D) architecture is adopted to encode the input image from one domain into the latent space \( z \) and decode it into the target domain. The embedding in the shared latent space \( z \) can be regarded as a compact, high-level embedding vector of a scene, while the encoded result \( E(I) \) can be considered as a particular sample in \( z \). With the shared latent space, \( E(I) \) is then reconstructed in a cross-domain or in-domain way with the corresponding decoder \( D \). The reconstructed image \( D(E(I)) \) is then sent to the discriminator (\( DIS \)) to be distinguished whether the generated images can be regarded as real images from the input domain. SubNetwork roles are analyzed to demonstrate how the proposed HazeGEN is different from prior work for the similar task such as [25]. Note that \( \{ E_h^s, D_h^s, DIS_h^s \} \) and \( \{ E_h^u, D_h^u, DIS_h^u \} \) are separately illustrated to distinguish the parameters iteratively updated by supervised and unsupervised learning, but they share the same sets of VAE-GAN modules.

In each \( GEN \) (see Fig. 4), the encoding part mainly contains two stride-2 convolutions and four residual blocks. We use the stride-convolution layer to down-sample the feature maps by \( 1/2 \). The decoding part consists of four residual blocks and two transposed convolutions. We use the transposed-convolution layer to up-sample the features by a factor of 2. A skip connection connects the encoder and decoder in the symmetric layer at different resolutions. The number of output channels are shown in Fig. 4. Each residual block consists of a convolution layer, an instance normalization layer (IN) [26], and a ReLU activation layer. The discriminator (see Fig. 5) is constructed with a convolution layer, an instance normalization layer, and a ReLU. Motivated by Pix2PixHD [27], the output is down-sampled to three scales to calculate the discriminator loss, which ensures the hierarchical feature similarity is reserved in the generated images.

B. Loss Function

The proposed semisupervised learning can be divided into two stages: the supervised training and the unsupervised training, which are performed in a step-by-step way. The whole process is illustrated in Algorithm 1.

1) Loss in Unsupervised Training Stage: The unsupervised training stage is supposed to extract real hazy distribution from unpaired real hazy images. In this stage, the real weather image
Fig. 3. The overall architecture of the HazeGEN which includes the VAE generator (GEN) and discriminator of GAN (DIS). GEN contains an encoder $E$ and a decoder $D$. $E$ and $D$ are connected by a code in the shared latent space $z$. Different connections of $E$ and $D$ are responsible for in-domain transformation (e.g., $I_{c-h} = D_h(E_h(I_c)))$ or cross-domain transformation (e.g., $I_{c-h} = D_h^c(E_h(I_c)))$. The shared modules for synthetic and real haze are separately illustrated to distinguish the parameters iteratively updated during the supervised and unsupervised stages, respectively.

$$L_{GEN}(I_{h,u}) = E \left[ \log \left( D_h^u(E_h(I_{h,u})) \right) \right] + E \left[ \log \left( 1 - D_h^s(E_h(I_{h,u})) \right) \right]. \quad (4)$$

The VAE optimizes the encoder by imposing a prior over the latent space $p(z)$, while making the decoded results $D_h^u(E_h(I_{h,u}))$ as close as possible to the original input $I_{h,u}$. $D_h^c(E_h(I_{h,u}))$ represents the latent space information $z$ encoded by $E_h$. The Kullback–Leibler divergence $D_{KL}$ evaluates the distance between the encoded distribution $q(E_h(I_{h,u}))[I_{h,u}]$ and the distribution prior of zero Gaussian $p(z)$. The last term in $L_{VAE}$ stands for in-domain $L_1$ loss to reconstruct the image with high fidelity.

To further improve the high-level tasks’ performance, we adopt the total variation (TV) loss in the unsupervised stage to encourage spatial smoothness, which can enhance visibility by removing unwanted details and preserving important details such as edges:

$$L_t = || \nabla_h D_h^u(E_h(I_{h,u})) ||_1 + || \nabla_v D_h^u(E_h(I_{h,u})) ||_1, \quad (5)$$

where $\nabla_h$ and $\nabla_v$ represent the horizontal and vertical differential operation matrices, respectively.
The total loss in unsupervised stage can be written as
\[ L_{\text{unspv}} = L_{\text{VAE/GAN}}(I_{h,s}) + \eta L_t \] (6)
where \( \eta \) is a hyperparameter that determines the contribution of the TV loss \( L_t \).

2) Loss in Supervised Training Stage: The main issue in the supervised stage is to learn the atmosphere scattering model in the paired training set, keep consistency between the inputs and avoid image ill-rendering caused by unsupervised training. To guide the transformation and learn valuable information, we employ VAE/GAN loss in the supervised stage
\[ L_{\text{VAE/GAN}}(I_{h,s}, I_c) = L_{\text{VAE}}(I_{h,s}) + L_{\text{GAN}}(I_{h,s}) + L_{\text{VAE}}(I_c) + L_{\text{GAN}}(I_c) \] (7)
where \( I_{h,s} \) and \( I_c \) stand for synthetic hazy image and its corresponding clean image, respectively. Cross-domain \( L_1 \) loss is adopted to ensure that the cross-domain transformed image \( D(E(I)) \) is close to the ground truth (i.e., the corresponding pixel-to-pixel paired haze/clean images before transformation)
\[ L_1 = \|D_h(E_c(I_c)) - I_{h,s}\|_1 + \|D_c(E_h(I_{h,s})) - I_c\|_1. \] (8)
The total loss function in supervised-learning stage is
\[ L_{\text{spv}} = L_{\text{VAE/GAN}}(I_{h,s}, I_c) + \beta L_1 \] (9)
where \( \beta \) reflects the importance of \( L_1 \).

3) Shared Loss in Both Training Stages: Since shared latent space assumption implies the cycle-consistency constraint [28], we employ cycle consistency loss in both supervised and unsupervised training stages to ensure that the reconstructed image generated by the in-domain and cross-domain encoder–decoder is the same as the original image
\[ L_{\text{cyc}} = \|D_c(E_h(D_h(E_c(I_c)))) - I_c\|_1 + \|D_h(E_c(D_c(E_h(I_{h,s}))))) - I_{h,s}\|_1 \] (10)
where \( E_h/D_h \) denotes the encoder/decoder for either synthetic or real haze domain.

Note that the loss mentioned above mainly deals with images’ similarity at the pixel level. The per-pixel losses do not capture perceptual differences between output and ground-truth images. Therefore, we apply perceptual loss which is based on a pretrained VGG-16 to measure the perceptual similarity in feature space
\[ L_p = \|\phi(D_c(E_h(I_{h,s}))) - \phi(I_c)\|_2 + \|\phi(D_h(E_c(I_c))) - \phi(I_h)\|_2 \] (11)
where \( \phi(\cdot) \) represents the feature maps obtained by the relu5_3 layers within the VGG-16 network. The total loss function can be expressed as
\[ L = L_{\text{unspv}} + L_{\text{spv}} + \delta L_{\text{cyc}} + \gamma L_p. \] (12)
The hyperparameters \( \delta \) and \( \gamma \) control the importance of the corresponding \( L_{\text{cyc}} \) and \( L_p \), respectively.

### IV. Application Study

In this section, we illustrate the effectiveness of our HazeGEN in two of the most common applications for autonomous driving, i.e., object detection and semantic segmentation. The datasets are generated based on the existing annotated clear day dataset. They are then used for training different backbones to improve these models’ performance in haze weather. Two widely used metrics, mean Intersection-Over-Union (mIoU) and mean Average Precision (mAP), are used to measure the performance. mIoU is the average intersection over union across all classes, which is the most commonly used metric for segmentation accuracy. Its formulation is
\[ \text{mIoU} = \frac{1}{n} \sum_{i=1}^{n} \frac{\text{TP}(i)}{\text{TP}(i) + \text{FP}(i) + \text{FN}(i)} \] (13)
where \( n \) is the total number of categories. \( TP, FP, \) and \( FN \) represent true-positive, false-positive, and false-negative predictions, respectively. mAP gives average accuracy of predicted object locations across all object predictions. Its definition is
\[ \text{mAP} = \frac{1}{n} \sum_{i=1}^{n} \text{AP}_k(i) \] (14)
Fig. 6. Visual comparisons of different generated datasets. The defects of other methods are labeled by red boxes. The “Supervised-only” generated haze can be barely seen and ill-rendering problems exist on the car logo. Haze synthesized by other methods of Foggy/Cityscapes is unnaturally concentrated, and their picture details are corrupted, which lead to lower detection/segmentation accuracy. In our method, the smoother distribution and better preserved details benefit the high-level vision tasks.

Algorithm 2: Details of the Semantic Segmentation.

**Train**

Input:
- Synthesized Cityscapes $I_{train}$ and its annotation $J_{train}$; Pre-trained MobileNetV3;

Output:
- Fine-tuned MobileNetV3;

Initialization:
- Fine-tuned epoch = 5; Optimizer = SGD;
- Learning rate = $10^{-6}$; Monument = 0.9;

Training:
- for $i=0$; $i < $ Fine-tuned epoch; $i + 1$ do
  $J'_{train} = $ MobileNetV3($I_{train}$);
  optimize MobileNetV3 with loss;

**Test**

Input:
- Real fog from Foggy Driving $I_{test}$;
- Synthesized fog from Foggy Cityscapes $I_{test}$;
- Fine-tuned MobileNetV3;

Output:
- Segmentation results $J_{test}$ and $J'_{test}$;

Test:
- $J_{test} = $ MobileNetV3($I_{test}$)
- $J'_{test} = $ MobileNetV3($I_{test}$)

where $n$ stands for the number of categories, and $AP_i$ is the average precision (AP) of the class $i$. Higher mIoU or mAP denotes better accuracy.

A. Implementations and Results for Dataset Generation

We train the proposed data generation network HazeGEN in Pytorch framework and use ADAM optimizer for training. The initial learning rate is 0.0001 and decreases by 0.75× every 30 000 iterations. The model is trained for 180 000 iterations until it gets convergence. The weight decay is set as 0.00001. The semisupervised training is performed by randomly sampling 4000 the labeled data from synthetic outdoor training set (the synthetic haze data used for supervised training stage) and 4000 unlabeled images from realistic hazy images in RESIDE [29] dataset (real haze data used for unsupervised training stage). The input images are resized to the size of $256 \times 256$. The data augmentation strategies, including horizontal and vertical flipping, and random cropping are applied. We follow [28] to preset the hyperparameters and then adjust them to get the best experimental results. After the adjustment, the loss weights are finally set as $\alpha = 1$, $\beta = 1000$, $\delta = 10$, $\gamma = 0.5$, and $\eta = 0.5$. The network is trained on the NVIDIA V100 GPU.

The visual results are shown in Fig. 6. It is worth mentioning that we observe that when more depth information is adopted (e.g., in Foggy-Cityscapes), the unnaturally concentrated haze distribution and corrupted details occur, which lead to lower detection/segmentation accuracy as will be demonstrated in the following experiments. In our generated images, by contrast, there are smoother fog distribution and better-preserved details after adding haze, so that they can truly facilitate high-level task performance improvement. The reason is that we propose a semisupervised training method that can learn from both real and synthetic haze images in an end-to-end way. As a result, instead of directly leveraging the depth information of the atmosphere scattering model, the optimal implicit depth prior is imposed by the learning algorithm automatically from the perspective of benefiting machine vision algorithms.

B. High-Level Task Performance on Real-World Images

To validate whether the proposed biGM can really meet the practical needs, we test semantic segmentation and object detection performance on images collected in real scenarios.

1) Segmentation: Overall, the pretrained segmentation model is finetuned with our generated haze dataset and previous synthetic haze dataset, and the comparisons are made to evaluate the finetuned models’ performance in real foggy weather. The details of the semantic segmentation experiments are shown in “Algorithm 2.”

The segmentation model DeepLabv3+[32] is constructed by using MobileNetV3 as the backbone. We adopt annotated dataset Cityscapes [33] as the basic clean image dataset to generate the corresponding foggy training set. Three representative data generation methods, atmosphere-scattering-model based FoHIS [34], depth-map-based Foggy-Cityscapes [5], and the more recent domain-adaptation-based TUNIT [30] are selected in comparisons. Besides, we make comparison with the simpler data augmentation methods of contrast reduction and the lately popular method of contrastive learning based segmentation method [31]. We test the fine-tuned MobileNetV3 model with Foggy Driving [5] dataset, which consists of a fine-annotation
Fig. 7. Visual comparisons of the segmentation. Our segmentation result is closest to the ground truth with all of the critical instances for automobile driving being successfully segmented. The predicting errors in the other methods are labeled by red boxes, among which the fire hydrant (the grey area) cannot be correctly predicted. Other works also have difficulty in distinguishing the pedestrian on the sidewalk (the red area).

Fig. 8. Visual comparisons for the object detection. We finetune the Faster-RCNN with different hazy datasets. It can be observed that the detection model finetuned by our hazy dataset is the closest to the detection ground truth under both light and dense haze distributions. Models trained by other hazy dataset make wrong predictions in real hazy weather.

Fig. 9. Our detection results on real-world haze-like images collected from the real autonomous driving system [35] to verify the generation capacity of the proposed model. We evaluate our detection system under different light and weather conditions.
TABLE I

<table>
<thead>
<tr>
<th>Category</th>
<th>Methods</th>
<th>Foggy Driving Fine (mAP / mIoU)</th>
<th>Time Cost (s)</th>
<th>Foggy Driving Coarse (mAP / mIoU)</th>
<th>Time Cost (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haze generation &amp; Retrain</td>
<td>Clean (baseline)</td>
<td>50.63/38.24</td>
<td>48.31/34.07</td>
<td>49.23/32.61</td>
<td>56.72/41.08</td>
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<td></td>
<td>Contrast Reduction (baseline2)</td>
<td>48.23/35.65</td>
<td>0.1205</td>
<td>48.39/35.87</td>
<td>0.1021</td>
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<tr>
<td></td>
<td>Ours</td>
<td>57.31/43.56</td>
<td>52.39/38.72</td>
<td>52.49/34.58</td>
<td>52.66/34.24</td>
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<td></td>
<td>Supervised-only</td>
<td>33.59/22.85</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>FoHIS-Cityscapes</td>
<td>47.75/35.23</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Foggy-Cityscapes</td>
<td>52.89/38.72</td>
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<td></td>
<td>TUNIT-Cityscapes [30]</td>
<td>52.03/34.62</td>
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<td>Dehaze &amp; Segmentation pipeline</td>
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<td>48.17/33.75</td>
<td>1.8270</td>
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</table>

![Fig. 10.](image)

Our generated dataset achieves the highest mAP compared to other works (even higher than RealHaze-Train on DenseHaze) as shown in (a), and has the closest accuracy compared to the RealHaze-Train (b). (a) Accuracy tested on DenseHaze and RealHaze-Test. The methods include training datasets or dehaze methods. (b) Per-Class Accuracy on dense synthetic haze (left) and real haze (right).

The main reason for our work’s superiority is that the previous synthetic datasets Foggy-Cityscapes and FoHIS-Cityscapes, and the images produced by “Supervised-only” learning are generated only by using atmosphere scattering model, which ignores the real hazy distribution. As for contrastive learning, it pays more attention to the high-level features instead of the pixel-level details, while the latter are necessary to build a hazy dataset that can well facilitate the segmentation task. By contrast, our method can better simulate the details and distribution of real-world hazy scenes owning to the semisupervised training strategy, which is effective in segmentation model finetuning.

Considering that dehazing is also one common way to preprocess hazy images for higher high-level task performance, we also conduct experiments with the state-of-the-art dehazing methods, MADN-dehaze [2] and FPA-dehaze [16]. The fog is removed via dehazing module before being put into the MobileNetV3. According to the Table I, our method outperforms the dehazing segmentation pipeline in both segmentation accuracy and processing speed since our method does not need the time-consuming preprocessing involved in dehazing method. This result proves that our method is more appropriate to be applied to real-time tasks for autonomous driving.

2) Details of the Object Detection: To validate the generalization capacity of the proposed work, we further evaluate the HazeGEN generated dataset on the object detection model.

Training and testing details are shown in Algorithm 3. We choose ResNet101-based Faster-RCNN as the detection model. FoHIS and HazeGEN methods are applied to synthesize HazeGEN-VOC and FoHIS-VOC foggy datasets based on VOC2007 dataset [36]. By using these datasets, we fine-tuned the pretrained Faster-RCNN to establish a stable CNN-based detector for haze weather. We evaluated the model’s detection accuracy on Real-world Task-driven Testing Set (RTTS) dataset, which has 4322 natural hazy images with five annotated object classes.

The experiment results are shown in Table II, Figs. 8 and 9, which prove that our method achieves satisfactory detection results in mAP and outperforms other dataset generation methods and the previous dehazing-detection methods. Fig. 8 shows that the models trained by other hazy datasets make too many wrong predictions, while ours makes satisfying predictions that are the closest to the ground truth for different haze distributions (under the same settings). Fig. 9 shows the promising detection results on images collected from real-world autonomous driving system [35] for another two haze-like conditions, dark snow dust and heavy snow. It can be observed that different light and weather conditions have tiny affect on our model’s detection.
Algorithm 3: Details of the Semantic Segmentation.

**Train**

**Input:**
- Synthesized VOC2007 \( I_{\text{train}} \) and its annotation \( J_{\text{train}} \); Pre-trained Faster-RCNN;

**Output:**
- Fine-tuned Faster-RCNN;

**Initialization:**
- Fine-tuned epoch = 5; Optimizer = SGD;
- Learning rate = \( 10^{-3} \); Monotonic = 0.9;

**Training:**

\[
\text{for } i = 0; i < \text{fine-tuned epoch}; i++ \text{ do } \]

\[
J'_{\text{train}} = \text{Faster-RCNN}(I_{\text{train}}); \]

- optimize Faster-RCNN with loss;

**Test**

**Input:**
- Real-world Task-driven Testing Set \( I_{\text{test}} \);
- Fine-tuned Faster-RCNN;

**Output:**
- Object detection results \( J_{\text{test}} \);

**Test:**

\[
J_{\text{test}} = \text{Faster-RCNN}(I_{\text{test}})\]

accuracy, which verifies the robustness of the proposed HazeGEN against domain shift. These results are consistent with those of segmentation, which demonstrates that the proposed innovations, the semisupervised learning and the shared latent space assumption for the VAE-GAN hybrid model, play an important part in improving high-level task performance.

C. Performance Compared With Real-World Collected Dataset for Challenging Industrial Scenarios

In this section, we evaluate different models’ detection mAP and per-class AP on two challenging industrial scenarios for comparison with the results of real-world collected haze dataset to validate whether our synthetic hazy dataset can be a substitute for the real-world dataset. These two scenarios are the real-world images that have diverse distributions (RealHaze-Test) from RTTS, and the dense synthetic haze images (DenseHaze) from Foggy-Cityscape.

In Fig. 10(a), it is obvious that the model trained on our dataset surpasses other models and has the closest accuracy with RealHaze-Train. Specifically, for the detection mAP on RealHaze-Test, ours surpasses its counterparts FoHIS and MADN-Dehaze by a performance increase as high as 10%. For dense haze testing, the model trained on our generated haze performs even better than the RealHaze-Train dataset.

D. Ablation Study

The ablation studies are performed to analyze how proposed training losses and model contribute to the improvement in high-level task performance in real scenarios. We remove the important losses or model components and evaluate their influences on the segmentation task as shown in Table III. It can be seen that the proposed/applied semisupervised losses and the important components do take effect in improving the final performance. Specifically, \( L_t \) for preserving important details in unsupervised training and \( L_p \) to measure the perceptual differences obviously improve the final performance. The advantages of the shared latent space assumption (evaluated by removing the cycle consistency loss \( L_{cpc} \) and \( L_t \) loss implied by this assumption) and the coupling of VAE and GAN (evaluated by removing the GAN loss \( L_{GAN} \)) are also demonstrated clearly.

V. Conclusion

In this article, we proposed an end-to-end dataset generation method to automatically generate training datasets for high-level tasks in hazy weather. We creatively combined the semisupervised training strategy, shared latent space, and coupled VAE-GAN to efficiently learn from both real-world haze results demonstrate that our generated dataset can be used to substitute RealHaze dataset in complex industrial scenarios with various haze densities.

To step further, from the perclass accuracy in Fig. 10(b), we can find that the model trained on our generated dataset has the closest accuracy to the model trained on the RealHaze-Train. By contrast, other methods have a large accuracy degradation compared with the model trained with real haze images. This demonstrates that our method can better simulate the characteristics of real haze, which means that the realistic HazeGEN-based produced images can be a good substitute for real-world annotated dataset, which greatly alleviates the expensive and time-consuming effort in collecting and annotating dataset for high-level tasks in adverse weather.
distribution and atmosphere modeling. Experiment results demonstrated significant performance improvement in various haze scenarios for the common high-level vision tasks of autonomous driving, i.e., the object detection and semantic segmentation. Compared with other methods, HazeGEN-based generated dataset can be a much better substitute for the real-world collected dataset, which demonstrates its great application potential in improving the safety of real autonomous driving systems.

REFERENCES


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