ForkGAN: Seeing into the Rainy Night (Supplementary Material)

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1 Semantic segmentation and object detection on stormy night data

To illustrate that our ForkGAN can boost semantic segmentation and object detection performance under stormy night conditions, we translate the stormy nighttime images from Alderley dataset [3] to the daytime images and perform semantic segmentation and object detection on the translated data. For segmentation, a model[4] pre-trained on Cityscapes dataset [2] is adopted. The differences of results on directly applying this model to the data before and after translation are shown in Fig. 1. The segmentation result on the raw stormy night image looks largely wrong. However, after the night-to-day translation using our ForkGAN, the segmentation becomes quite reasonable with accurate detailed information.

For object detection, our ForkCAN can also boost the performance significantly, especially for objects in the dark or occluded, as shown in Fig. 1. We detect cars, trucks, persons, traffic signs and traffic signals using a detector pre-trained on BDD100K dataset [4]. Directly performing detection on the rainy night image can easily miss the targets and generate false positives due to low-lighting, reflection and blurring. After the night-to-day translation, we can obtain more accurate detection outputs on the reasonable translated daytime images.

To show more results, we also provide a video showing the translation and segmentation results on continuous sequences from the challenging Alderley dataset.

2 High-resolution night-to-day image translation

In order to show that our ForkGAN can handle high-resolution image translation, we perform the challenging night-to-day task on the BDD100K dataset [4] and show representative translation results in Fig. 2. As shown, our method can capture and enhance the detailed information (e.g., the letters on the billboard in the darkness), which is helpful for boosting the performance of other vision tasks. We also present representative segmentation outputs on the translated daytime images in Fig. 3. The before-after comparison clearly shows that ForkGAN can

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[4] https://github.com/srihari-humbarwadi/DeepLabV3_Plus-Tensorflow2.0

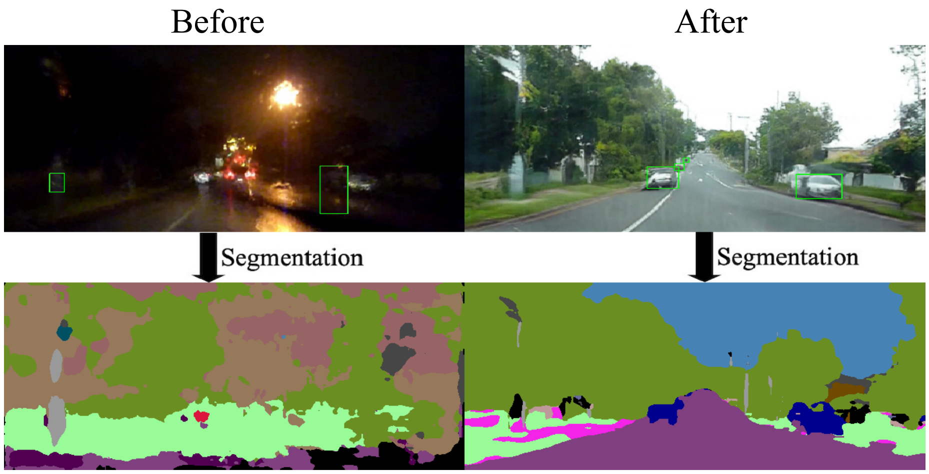

Fig. 1. For the semantic segmentation task, we apply a segmentation model pre-trained on Cityscapes dataset [2] to both the image before and after translation. Our ForkGAN can significantly improve the accuracy of segmentation. As for object detection, we adopt the pre-trained faster-rcnn-r50-fpn-1x model based on MMDetection [1] to detect cars, trucks, persons, traffic signs and traffic signals. Due to low-light visibility and reflection of light, the detection performance on raw rainy night images is extremely bad. It cannot provide reliable bounding box outputs. After the night-to-day translation, our ForkGAN preserves and enhances the object information and leads to more accurate detection outputs.

significantly boost the semantic segmentation performance on high-resolution data.

Fig. 2. The visual night-to-day image translation results on the BDD100K dataset [4]. Some details worth attention are indicated by yellow arrows. Best viewed in color.

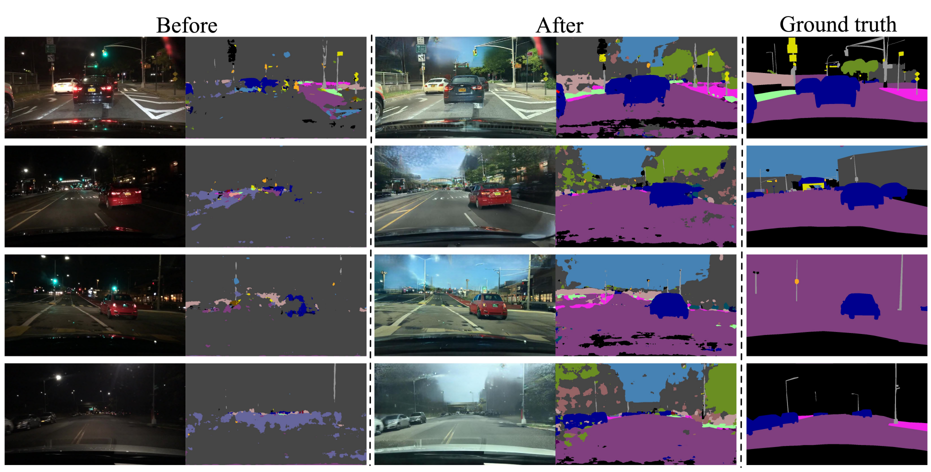

Fig. 3. The visual night-to-day image translation results and corresponding segmentation outputs on the BDD100K dataset [4], in comparison with the ground-truths.

References

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