Learning of Image Dehazing Models for Segmentation Tasks

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Introduction

We are proposing a novel end-to-end approach for image dehazing, fit for being used as input to an image segmentation procedure, while maintaining the visual quality of the generated images. Inspired by the success of GAN, we propose to optimize the generator by introducing a discriminator network and a loss function that evaluates segmentation quality of dehazed images. In addition, we make use of a supplementary loss function that verifies that the visual and the perceptual quality of the generated image are preserved in hazy conditions.

Motivations :

- There is a need to make dehazing for **subsequent tasks**. Dehazing approaches generally rely on distance measures between the generated image and its corresponding ground truth.

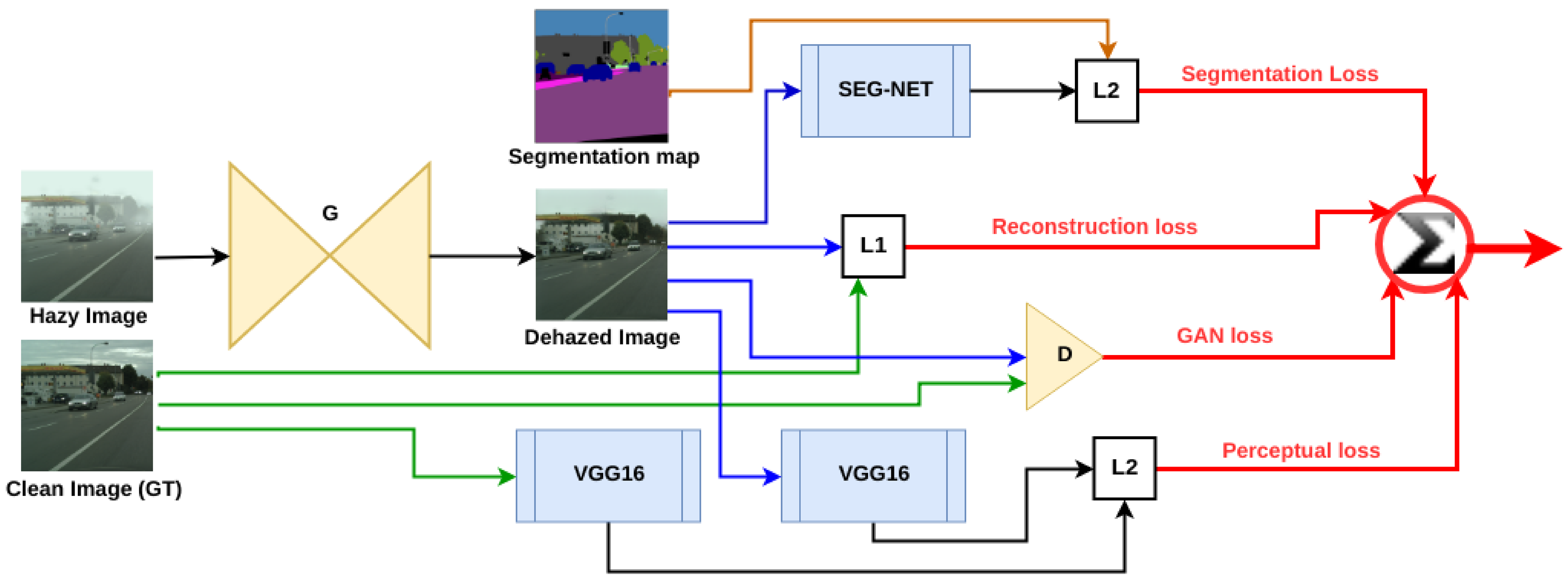
Related work :

- Sakaridis et al. (2018) : Semantic foggy scene understanding with synthetic data
- Liu et al. (2018) : When image denoising meets high-level vision tasks : A deep learning approach

Goals :

- **Evaluate the impact** of SOTA dehazing model on segmentation tasks.
- **Provide** a dehazing network toward segmentation tasks.
- **Evaluate the gain** of the segmentation loss in the dehazing model on segmentation tasks.

Dehazing for segmentation's network



The **loss function of the generator** for the network is :

$$L_{generator} = L_{GAN} + \lambda_1 L_{pixel} + \lambda_2 L_{percep} + \lambda_3 L_{seg}. \quad (1)$$

- L_{GAN} is the loss function from pix2pix used to generate fake images.
- L_{pixel} is the reconstruction loss between the ground truth for dehazing (a.k.a. the real image) and the fake dehazed image, based on their individual pixel values, allowing the network to produce crisper images.
- L_{percep} is the perceptual loss used for preserving important semantic elements of the image in the output of the generator. It's improves the quality of the output by relying on the high-level representation features of a neural network
- L_{seg}, the segmentation loss, computed by placing the output of the generator (i.e., the dehazed image) into the segmentation network (SEG-NET). The obtained segmentation map is then compared to the ground truth segmentation map, using the L_2 loss.

  Basically, the model tries at the same time to remove haze as much as possible while preserving, or even improving segmentation performance.

Experiments

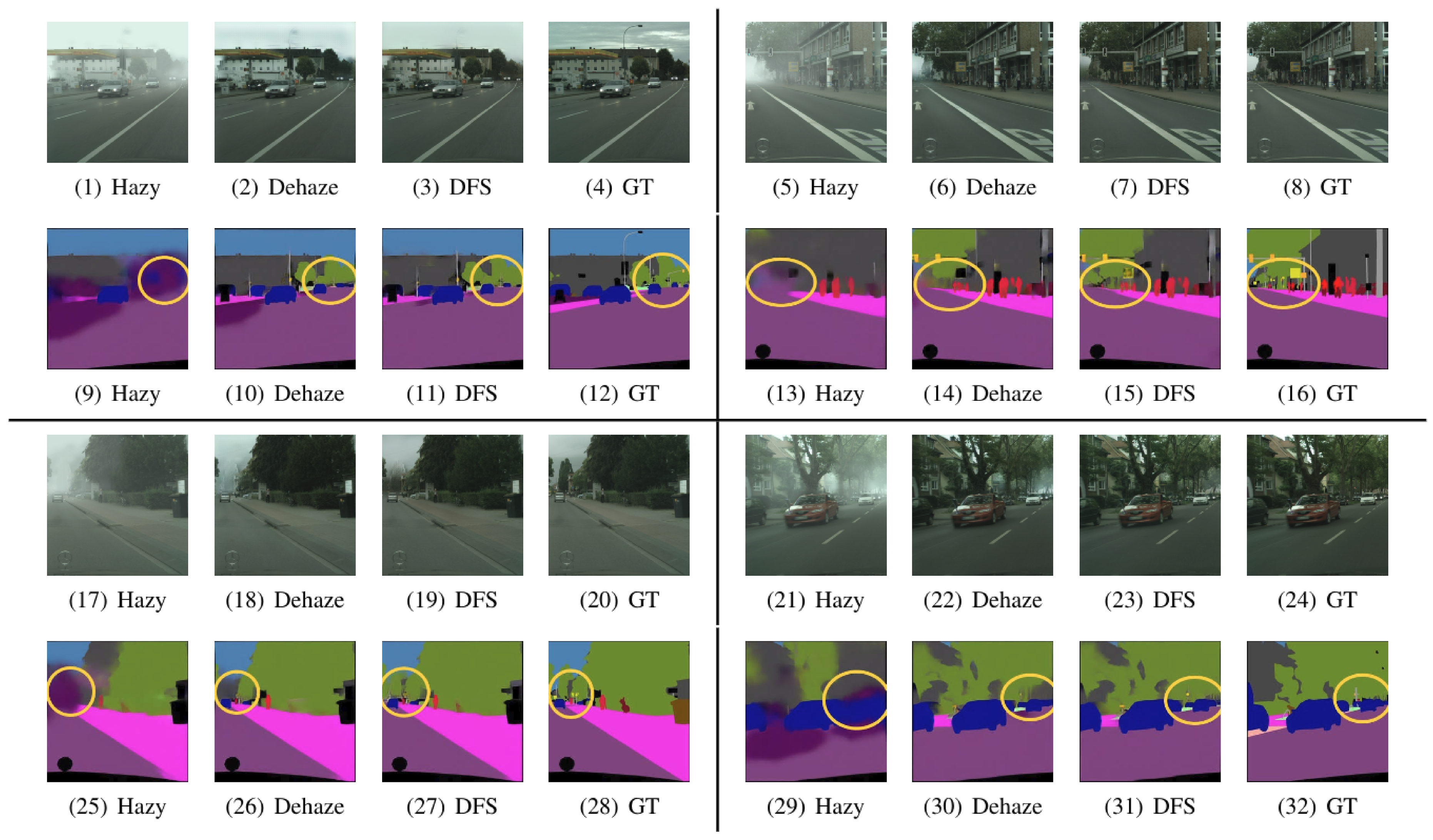
Single image dehazing :

- Building a dehazing model and make sure it's comparable with the SOTA in dehazing.
  - Using D-Hazy dataset (hazy NYU Depth Dataset V2).
  - 80% of the dataset for training, 20% for testing.
  - 200 epochs, batch size of 16, ADAM as the optimizer, NVIDIA GTX 1080Ti

Dehazing for segmentation :

- Building a dehazing model with a segmentation loss and compare it to the SOTA of dehazing.
  - Using Foggy Cityscape (hazy Cityscape).
  - Data separated in training/validation/test set.
  - 200 epochs, batch size of 16, ADAM as the optimizer, NVIDIA GTX 1080Ti
  - The segmentation network used to compute the segmentation loss is a pix2pix trained for segmentation on Cityscape (not overlapping with foggy Cityscape).

Examples



Qualitative examples on several images with haze. We can see that using segmentation loss improved the quality of the dehazing and also of the subsequent segmentation. Segmentation is done using the SEG-NET, except for the GT segmentation map which is the ground truth, not the output of the SEG-NET.

Results

- Results on the test set with SEG-NET segmentation

Metrics	Hazy	Dehaze	DFS	GT
PSNR	11.95	14.77	**15.36**	*15.45*
SSIM	0.624	0.727	**0.747**	*0.748*

- Results on the test set with DeepLabv3 segmentation

Metrics	Hazy	Dehaze	DFS	GT
IoU-cl	0.556	0.553	0.557	*0.570*
iIoU-cl	0.294	0.309	**0.316**	*0.340*
IoU-ca	0.745	0.774	0.775	*0.794*
iIoU-ca	0.518	0.554	**0.569**	*0.627*

Conclusion

Discussion :

- This work demonstrates the **usefulness of including segmentation loss** in an end-to-end training of deep learning models for dehazing.
- The learning-based dehazing model is **generated not just for denoising metrics**, but also with an optimization criterion aimed at achieving something useful for a specific task.

Future works :

- We can consider to boost even more the performance of DFS **using directly an approximation of the IoU/iIoU measures** for gradient descent, which are better optimization measure than mean square error and similar.
- Test this network logic on **other problems** (i.e., desnowing and deraining) and tasks (i.e., detection, classification and tracking).