Towards Artifact-Free Image Defogging

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Defogging

Defogging (or dehazing) is the task of removing the fog from an input image, aimed at reconstructing the same scene as if it were taken in good weather conditions.

- Easier with stereo images or a 3D reconstruction of the scene (e.g., LIDAR).
- More difficult with single images, especially in presence of severe fog.

Useful in:

- Autonomous driving.
- Security.
- Improving photographs aesthetics.
- ...

↓

Current approaches and problems

Classical methods [1]–[3] are often surpassed by DNN-based ones [4]–[8], using CNN or GANs. However, they often require paired data.

Problems

- Impossible to obtain the same identical scene with and without fog.
- Often, fog is inserted artificially in the training images.
  - Not precise since the exact depth map is needed.
  - Synthetic fog $\neq$ real fog.

Totally unpaired approaches [9] show promising results in real fog conditions.

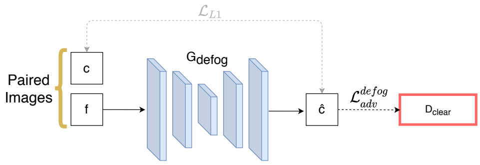
Problems

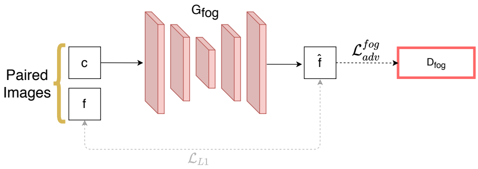
- Models often insert unwanted artifacts in the defogged images.
  - Due to the unrestricted nature of the unpaired training.

CurL-Defog (Curriculum Learning Defog)

- Goal: use real foggy images but limit as much as possible the insertion of artifacts.
- We use a curriculum learning [10] strategy.
  - First, model is trained with paired data → artifact insertion highly penalized.
  - Then, real images are used → high quality on real fog.
- Gradual transition between paired and unpaired data.
- Model can be seen as:
  - Paired training → two different pix2pix models [11].
  - Unpaired training → unique cycleGAN model [12].

CurL-Defog (Curriculum Learning Defog)





$$\mathcal{L}_{adv}^{defog} = (D_{clear}(c))^2 + (D_{clear}(G_{defog}(f)) - 1)^2$$

$$\mathcal{L}_{adv}^{fog} = (D_{fog}(f))^2 + (D_{fog}(G_{fog}(c)) - 1)^2$$

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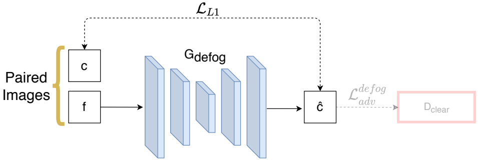
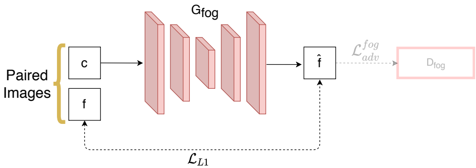
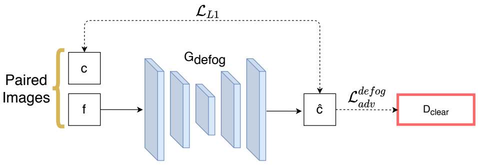
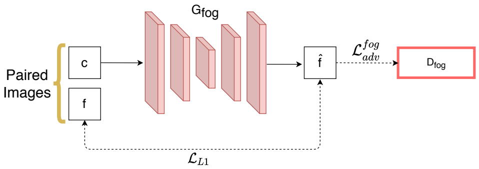




$$\mathcal{L}_{adv}^{defog} = (D_{clear}(c))^2 + (D_{clear}(G_{defog}(f)) - 1)^2 \qquad \mathcal{L}_{adv}^{fog} = (D_{fog}(f))^2 + (D_{fog}(G_{fog}(c)) - 1)^2$$

$$\mathcal{L}_{L1} = \| G_{defog}(f) - c \|_1 + \| G_{fog}(c) - f \|_1$$



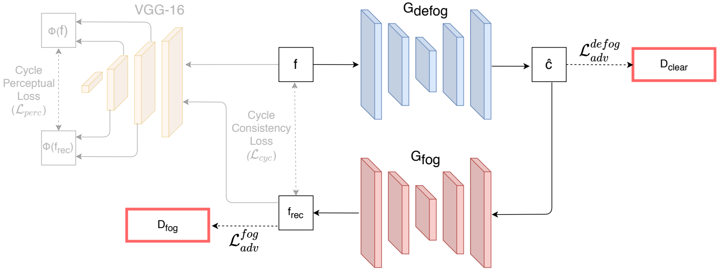


$$\mathcal{L}_{adv}^{defog} = (D_{clear}(c))^2 + (D_{clear}(G_{defog}(f)) - 1)^2 \qquad \mathcal{L}_{adv}^{fog} = (D_{fog}(f))^2 + (D_{fog}(G_{fog}(c)) - 1)^2$$

$$\mathcal{L}_{L1} = \|G_{defog}(f) - c\|_1 + \|G_{fog}(c) - f\|_1$$

$$\mathcal{L}_{pair} = \mathcal{L}_{adv}^{defog} + \mathcal{L}_{adv}^{fog} + \lambda_{L1}\mathcal{L}_{L1}$$

CurL-Defog (Curriculum Learning Defog)



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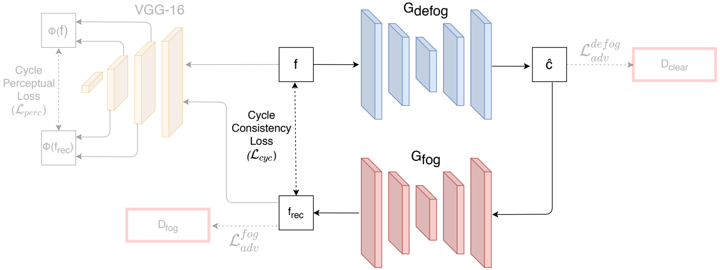

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$$\mathcal{L}_{cyc} = \| G_{fog}(G_{defog}(f)) - f \|_1 + \| G_{defog}(G_{fog}(c)) - c \|_1$$

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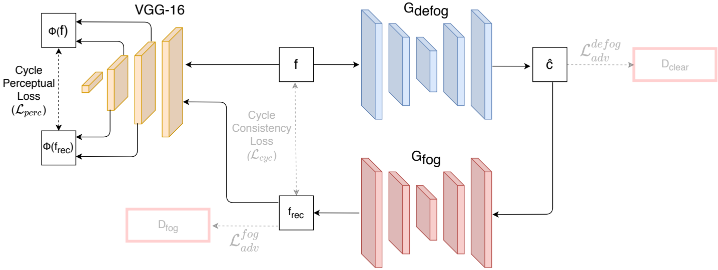
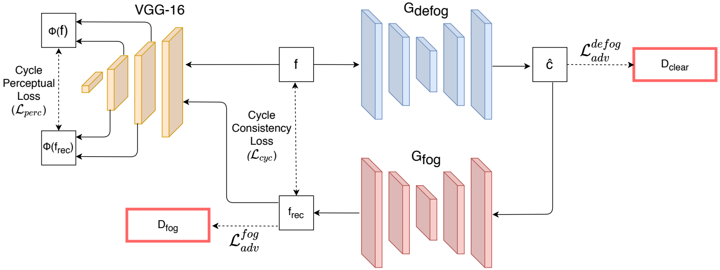


$$\mathcal{L}_{adv}^{defog} = (D_{clear}(c))^2 + (D_{clear}(G_{defog}(f)) - 1)^2 \qquad \mathcal{L}_{adv}^{fog} = (D_{fog}(f))^2 + (D_{fog}(G_{fog}(c)) - 1)^2$$

$$\mathcal{L}_{cyc} = \|G_{fog}(G_{defog}(f)) - f\|_1 + \|G_{defog}(G_{fog}(c)) - c\|_1$$

$$\mathcal{L}_{perc} = \|\phi(f) - \phi(G_{fog}(G_{defog}(f)))\|_2^2 + \|\phi(c) - \phi(G_{defog}(G_{fog}(c)))\|_2^2$$



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$$\mathcal{L}_{unpair} = \mathcal{L}_{adv}^{defog} + \mathcal{L}_{adv}^{fog} + \lambda_{cyc}\mathcal{L}_{cyc} + \lambda_{perc}\mathcal{L}_{perc} + \lambda_{idt}\mathcal{L}_{idt}$$

HArD (Haze Artifact Detector)

- No defogging metrics takes into account the presence of artifacts.
- Some metrics may be deceived by the presence of artifacts.
  - E.g. the metrics that counts the number of visible edges [13].
- How to detect the insertion of artifacts without the ground truth real images?
  - Idea: no edges in the foggy image → no edges in the defogged image.
  - Find the regions in both images that contains edges and compare them.
  - Regions with edges in the defogged image and not in the foggy one → artifacts.

Algorithm 1 HArD pseudocode

Require: f = original foggy image
Require: d = defogged image

procedure $\textsc{HArD}(f, d)$
  $f' \leftarrow \textsc{Prewitt}(f_{gray})$
  $d' \leftarrow \textsc{Prewitt}(d_{gray})$
  $f'_{smooth} \leftarrow \textsc{GaussianFilter}(f')$
  $d'_{smooth} \leftarrow \textsc{GaussianFilter}(d')$
  $f'_{scaled} \leftarrow \textsc{Normalize}(f'_{smooth})$
  $f'_{sat} \leftarrow \tanh(\nu_{fog} \cdot f'_{scaled})$
  $d'_{scaled} \leftarrow \textsc{Normalize}(d'_{smooth})$
  $d'_{sat} \leftarrow \tanh(\nu_{defog} \cdot d'_{scaled})$
  $diff \leftarrow \min(0, d'_{scaled} - f'_{sat})$
  return $\textsc{Mean}(diff)$
end procedure

HArD (Haze Artifact Detector)

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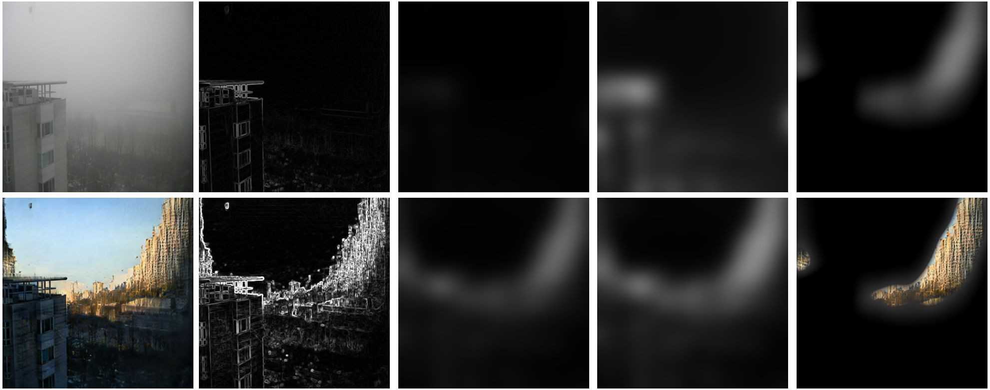


Input images | Prewitt | Gaussian smoothing | Saturation | Difference

Experiments on synthetic data

- Comparison with SOTA method that use paired data.
- All method trained on OTS synthetic dataset [14].
- Real training dataset (for CurL-Defog): LIVE Image Defogging [15].
- Test dataset: HSTS synthetic dataset [14].

	DCP [3]	CAP [1]	NLD [2]	DehazeNet [4]
PSNR	14.84	21.53	18.92	24.48
SSIM	0.7609	0.8727	0.7411	**0.9183**

	MSCNN [6]	AOD-Net [5]	Pix2Pix [11]	**CurL-Defog**
PSNR	18.64	20.55	24.22	**24.83**
SSIM	0.8168	0.8973	0.8991	0.9037

Experiments on real data

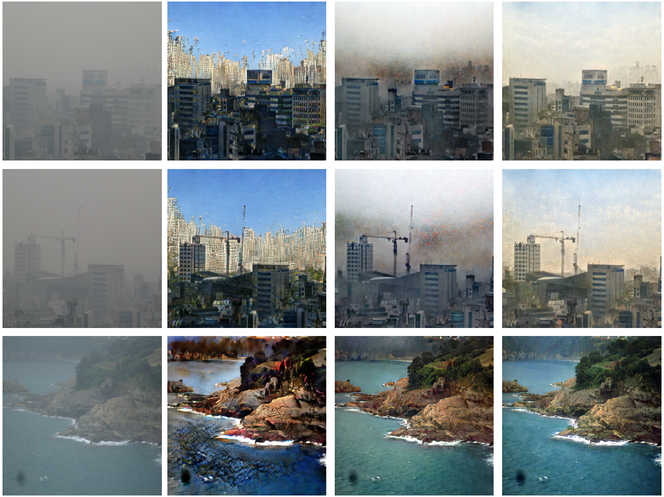
- Synthetic dataset: OTS [14].
- Real Dataset: LIVE Image Defog real dataset [15].
- Test dataset: LIVE Image Defog real test set [15].

	CycleDehaze [9]	Pix2Pix [11]	**CurL-Defog**
e (↑)	32.70	25.74	28.41
$\bar{r}$ (↑)	3.290	2.135	2.636
HArD (↓)	2.535	0.3786	1.374

Experiments on severe fog

- Synthetic dataset: OTS [14].
- Real Dataset: O-Haze dataset [16].
- Test dataset: Dense-Haze dataset [17].

	MSCNN [6]	DehazeNet [4]	CycleDehaze [9]	Pix2Pix [11]	**CurL-Defog**
PSNR	**12.52**	11.36	10.54	10.55	12.24
SSIM	0.369	0.374	0.261	0.311	**0.469**



Foggy image | CycleDehaze [9] | Pix2Pix [11] | **CurL-Defog**

Conclusions and Future Work

Conclusions

- CurL-Defog: a curriculum learning-based novel defogging method.
- Artifacts minimized while maintaining good quality on real images.
- Effective defogging even with severe fog.
- A new referenceless metric (HArD) to numerically estimate the amount of defogging artifacts.

Future Work

- Combine the HArD metric with other defogging metrics (e.g. [13]) in order to penalize the insertion of artifacts.
- Use the HArD metric as a loss function during training.
- Scale the CurL-Defog method to HD images or videos.

Thank you
for your attention

Bibliography

[1] Q. Zhu, J. Mai, and L. Shao, "A fast single image haze removal algorithm using color attenuation prior," *IEEE transactions on image processing*, vol. 24, no. 11, pp. 3522–3533, 2015.

[2] D. Berman, S. Avidan, *et al.*, "Non-local image dehazing," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 1674–1682.

[3] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," *IEEE transactions on pattern analysis and machine intelligence*, vol. 33, no. 12, pp. 2341–2353, 2010.

[4] B. Cai, X. Xu, K. Jia, C. Qing, and D. Tao, "Dehazenet: An end-to-end system for single image haze removal," *IEEE Transactions on Image Processing*, vol. 25, no. 11, pp. 5187–5198, 2016.

[5] B. Li, X. Peng, Z. Wang, J. Xu, and D. Feng, "Aod-net: All-in-one dehazing network," in *Proceedings of the IEEE International Conference on Computer Vision*, 2017, pp. 4770–4778.

[6] W. Ren, S. Liu, H. Zhang, J. Pan, X. Cao, and M.-H. Yang, "Single image dehazing via multi-scale convolutional neural networks," in *European conference on computer vision*, Springer, 2016, pp. 154–169.

[7] Y. Pang, J. Xie, and X. Li, "Visual haze removal by a unified generative adversarial network," *IEEE Transactions on Circuits and Systems for Video Technology*, pp. 1–1, 2018, ISSN: 1051-8215.

[8] R. Li, J. Pan, Z. Li, and J. Tang, "Single image dehazing via conditional generative adversarial network," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Jun. 2018, pp. 8202–8211.

[9] D. Engin, A. Genç, and H. K. Ekenel, "Cycle-dehaze: Enhanced cyclegan for single image dehazing," in *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, 2018.

[10] Y. Bengio, J. Louradour, R. Collobert, and J. Weston, "Curriculum learning," in *Proceedings of the 26th International Conference on Machine Learning*, 2009, pp. 41–48.

[11] P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, "Image-to-image translation with conditional adversarial networks," *arxiv*, 2016.

[12] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, "Unpaired image-to-image translation using cycle-consistent adversarial networks," in *Computer Vision (ICCV), 2017 IEEE International Conference on Computer Vision*, 2017.

[13] N. Hautiere, J.-P. Tarel, D. Aubert, and E. Dumont, "Blind contrast enhancement assessment by gradient ratioing at visible edges," *Image Analysis & Stereology*, vol. 27, no. 2, pp. 87–95, 2011.

[14] B. Li, W. Ren, D. Fu, D. Tao, D. Feng, W. Zeng, and Z. Wang, "Benchmarking single-image dehazing and beyond," *IEEE Transactions on Image Processing*, vol. 28, no. 1, pp. 492–505, 2019.

[15] L. K. Choi, J. You, and A. C. Bovik, *Live image defogging database*, http://live.ece.utexas.edu/research/fog/fade_defade.html, Accessed: 2019-05-30.

[16] C. O. Ancuti, C. Ancuti, R. Timofte, and C. De Vleeschouwer, "O-haze: A dehazing benchmark with real hazy and haze-free outdoor images," in *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, 2018, pp. 754–762.

[17] C. O. Ancuti, C. Ancuti, M. Sbert, and R. Timofte, "Dense haze: A benchmark for image dehazing with dense-haze and haze-free images," in *IEEE International Conference on Image Processing (ICIP)*, ser. IEEE ICIP 2019, Taipei, Taiwan, 2019.