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Enhanced CycleGAN Dehazing Network

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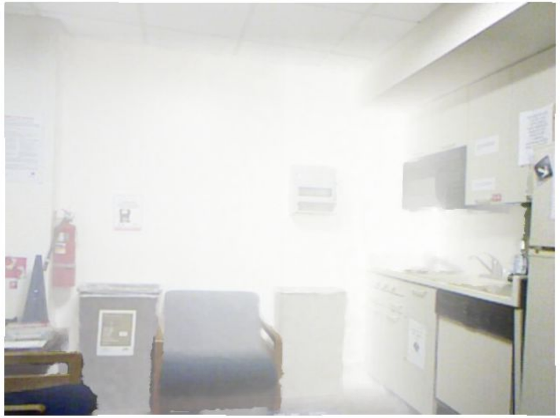
Single Image Dehazing Problem

- Haze degrades **visibility** and **image quality**
  - Degrades the performance of computer vision tasks, e.g., object detection
- **Goal**: Reconstruct haze-free image of a hazy image



Hazy

Haze-free/Ground truth

Motivation

Object detection on the hazy image(left) and its enhanced/dehazed counterpart(right)

Unpaired Image Dehazing

- No hazy-clean pairs are available
- No ground truth is available
- The training is done using unpaired supervision

Motivation

- It is almost impossible to simultaneously capture corrupted and ground truth images of the same visual scene (e.g., hazy and haze-free image pairs)
- Synthesizing corrupted images are usually not photo-realistic enough, leading to various artifacts when the trained model is applied to real-world hazy images

Dehazing Methods

- We can categorize them into two categories:
  - Prior based
    - Mainly based on the parameter estimation of atmospheric scattering model
    - The physical scattering model consists of the transmission map and the atmospheric light:
      - $I(x) = J(x)\mathbf{t}(x) + \mathbf{A}(1 - \mathbf{t}(x))$
      - I(x) is the hazy image, J(x) is the haze-free image, t(x) is the medium transmission map, and A is the global atmospheric light on each x pixel coordinates
    - The solution of the haze-free image depends on the **estimation of the atmospheric light and the transmission map**

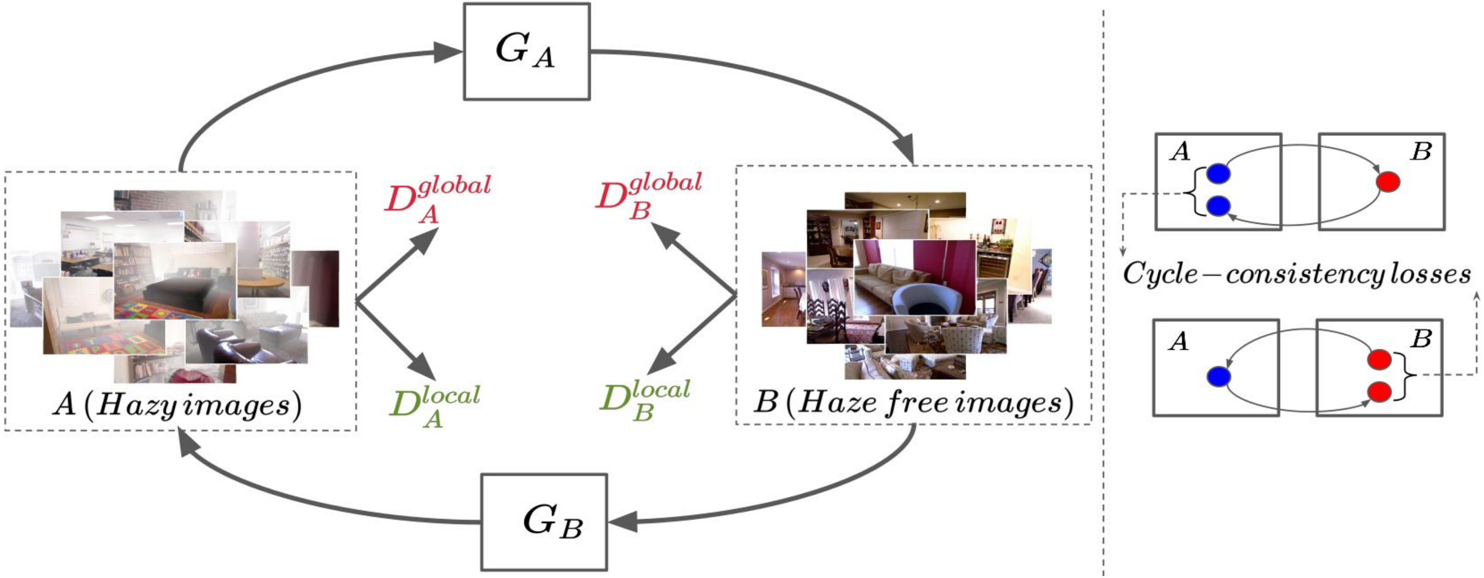
Dehazing Methods

- We can categorize them into two categories:
  - Prior based
  - Learning based/data-driven: Utilizes the deep convolutional neural networks or generative adversarial networks to estimate the transmission map indirectly
    - Takes advantage of the power of data
    - Paired vs unpaired supervision: Paired single image dehazing methods need the **haze-free/ground truth** of each hazy image for training, unpaired dehazing methods **do not require the haze-free pair** of the hazy images
  - combination methods:
    - Take advantage of deep CNNs/GANs and uses priors jointly

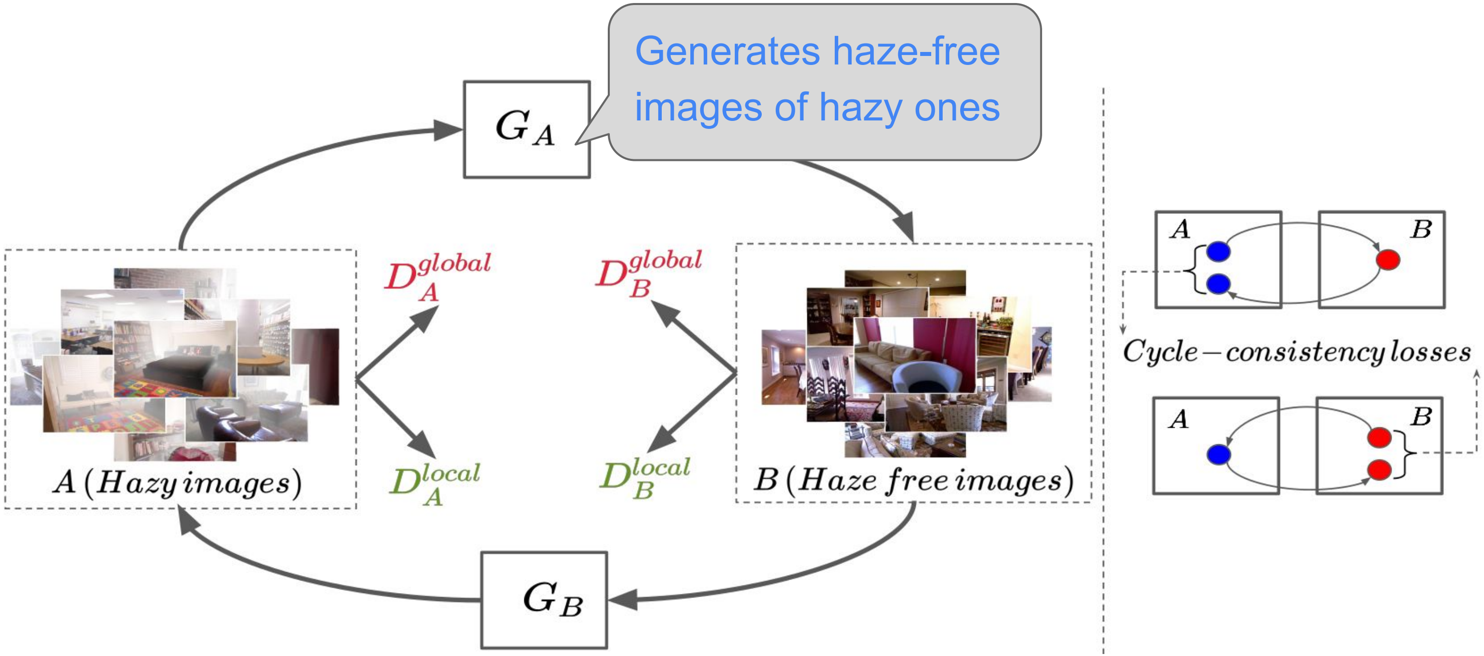
Our Approach

- We reduce the unpaired image dehazing to an **image-to-image translation** problem
- We improve CycleGAN in different aspects for dehazing purpose.
    - We employ a **global-local discriminator structure** to deal with spatially varying non-homogeneous haze.
    - **We define self-regularized color loss** and utilize it along with perceptual loss to generate more realistic and visually pleasing images.
    - We use an **encoder-decoder architecture** with residual blocks in the generator with skip connections so that the network better preserves the details
- We call this network **ECDN** (Enhanced CycleGAN Dehazing Network)

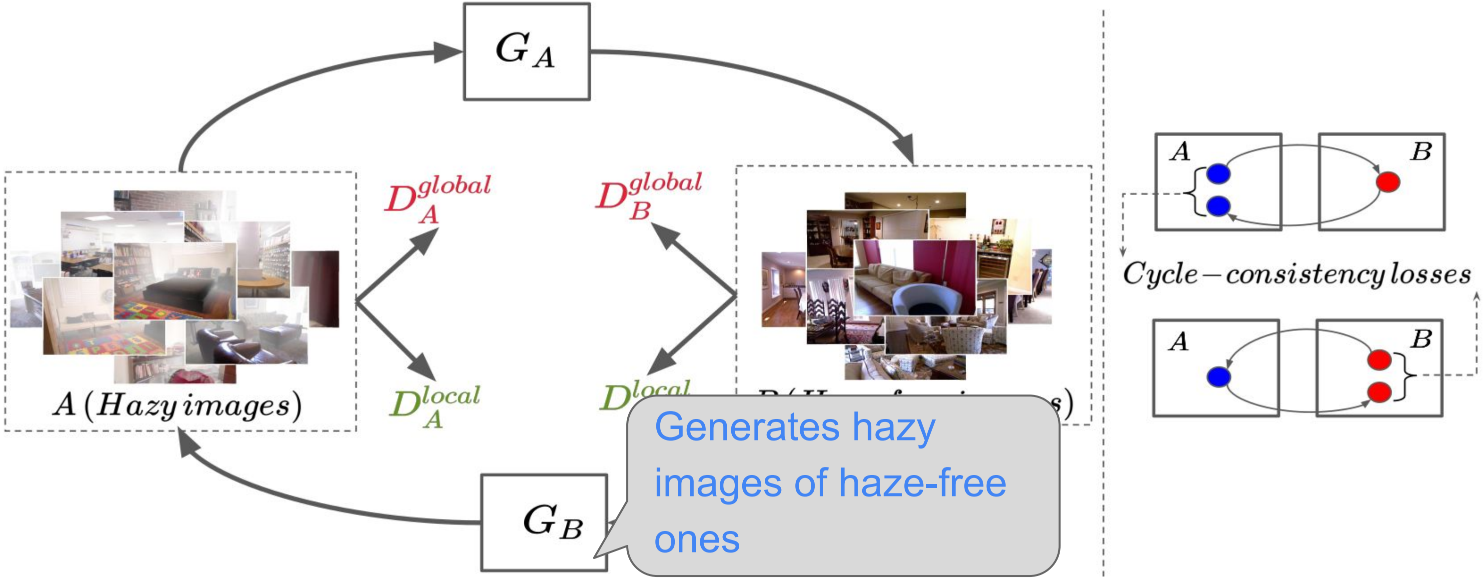
Overview of ECDN



Overview of ECDN



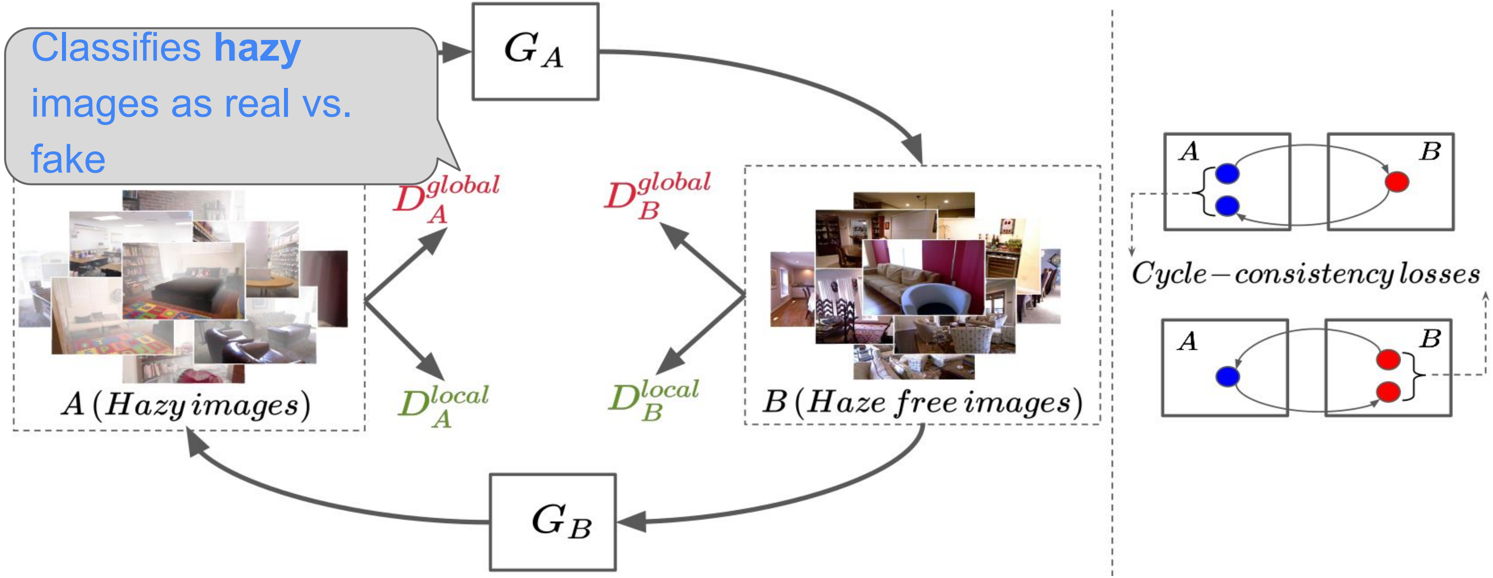
Overview of ECDN



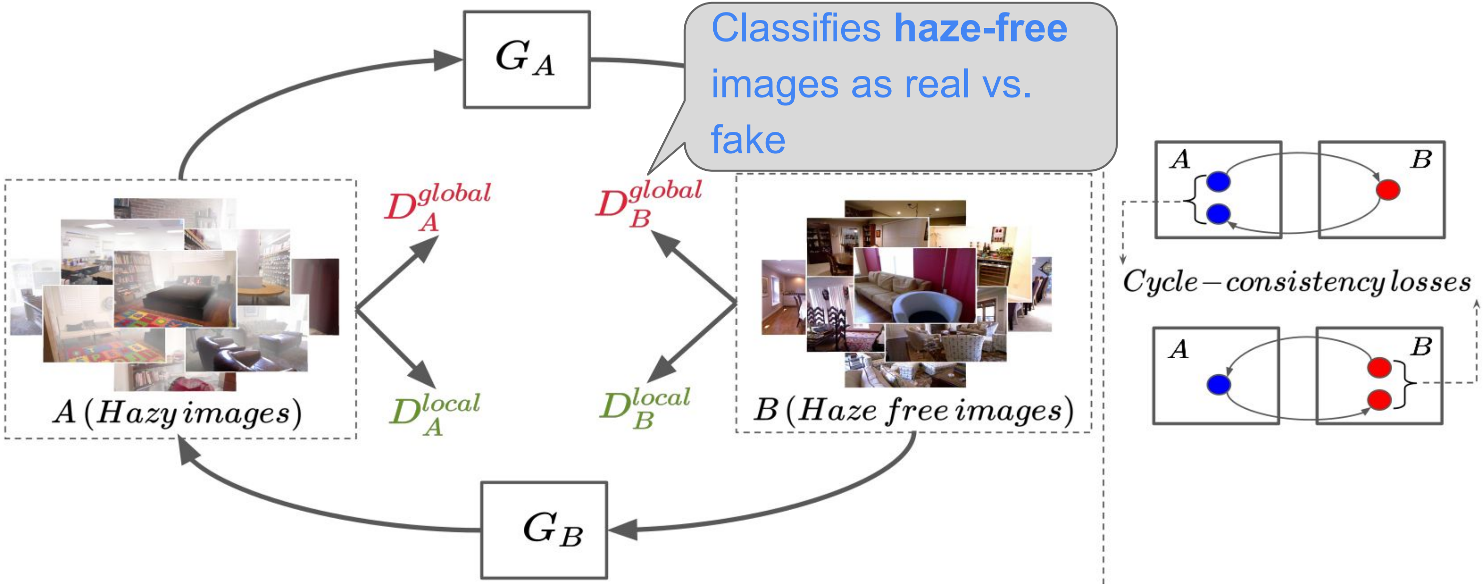
Generates hazy images of haze-free ones

Overview of ECDN

Classifies **hazy** images as real vs. fake

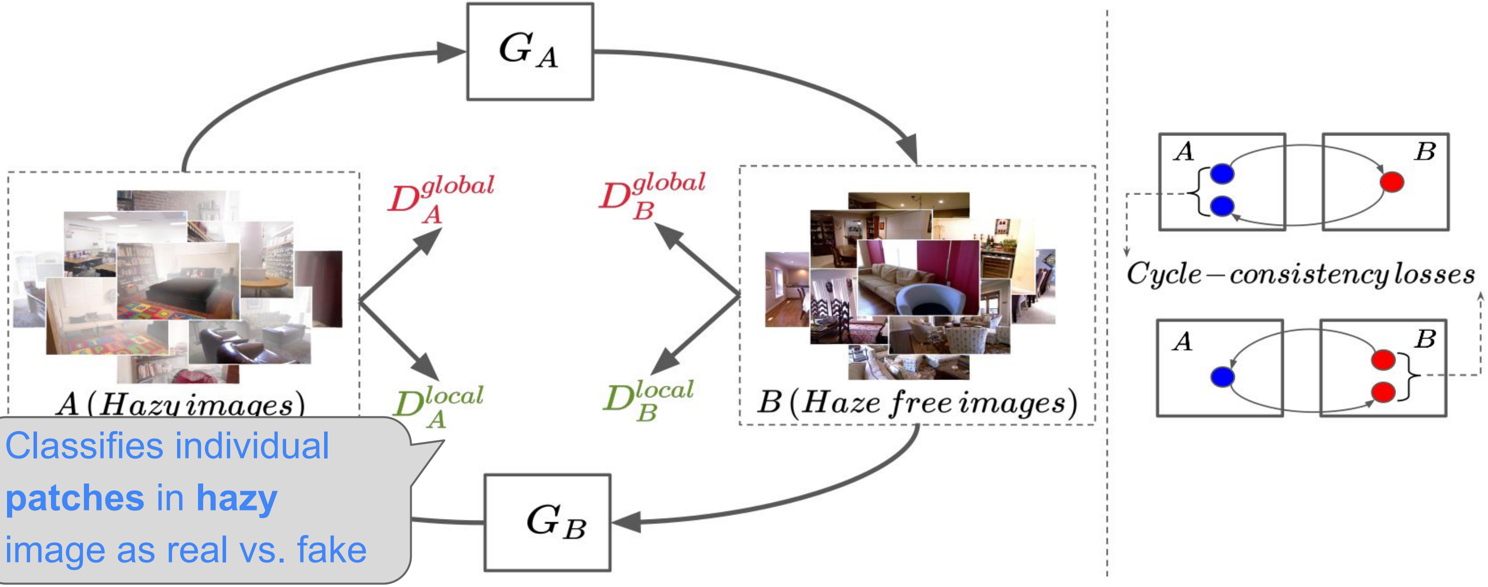


Overview of ECDN



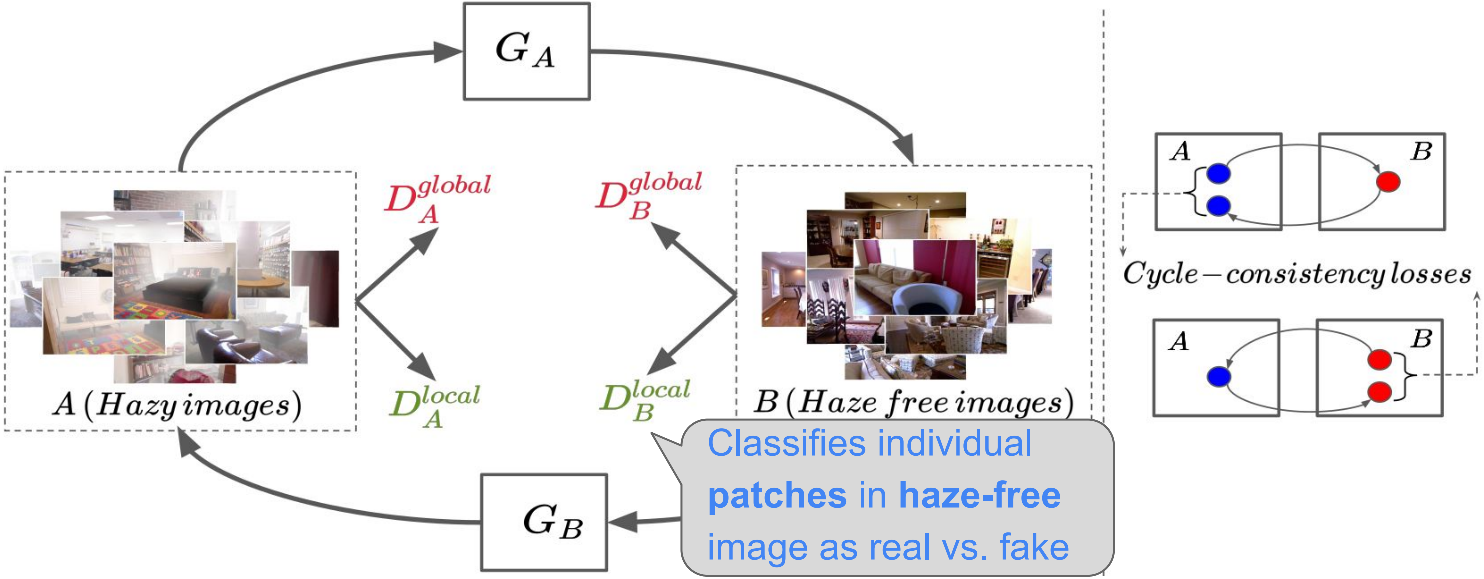
Classifies **haze-free** images as real vs. fake

Overview of ECDN



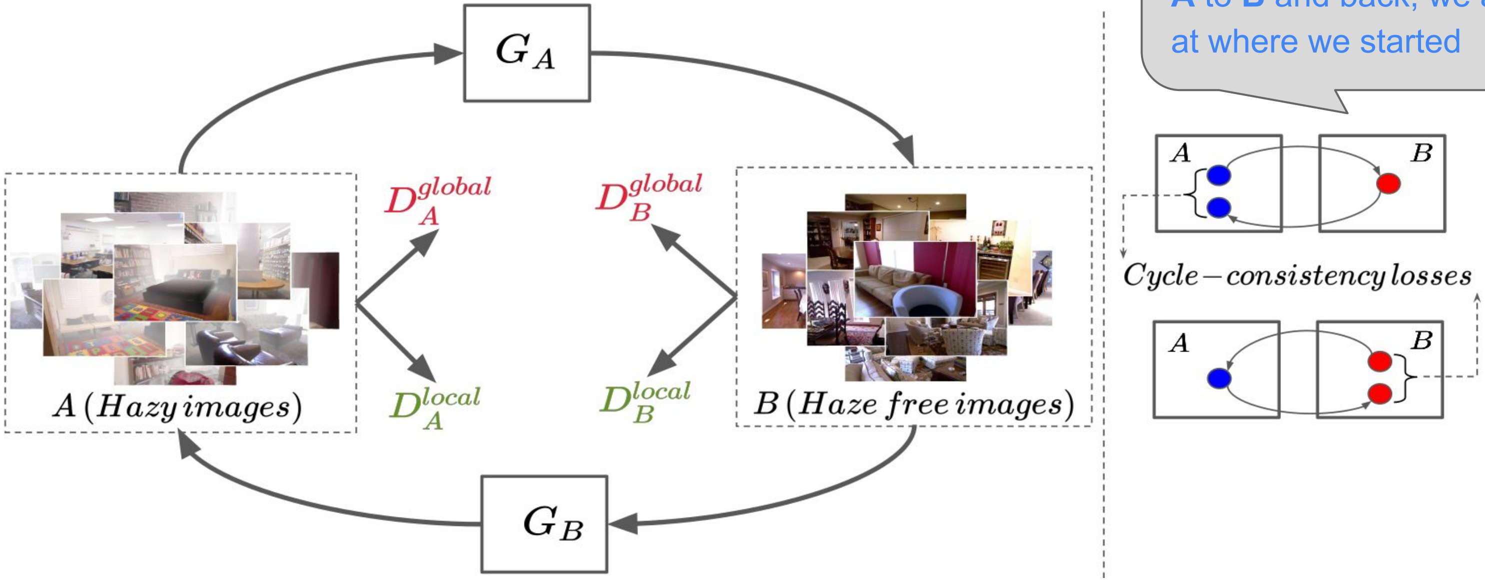
Classifies individual **patches** in **hazy** image as real vs. fake

Overview of ECDN

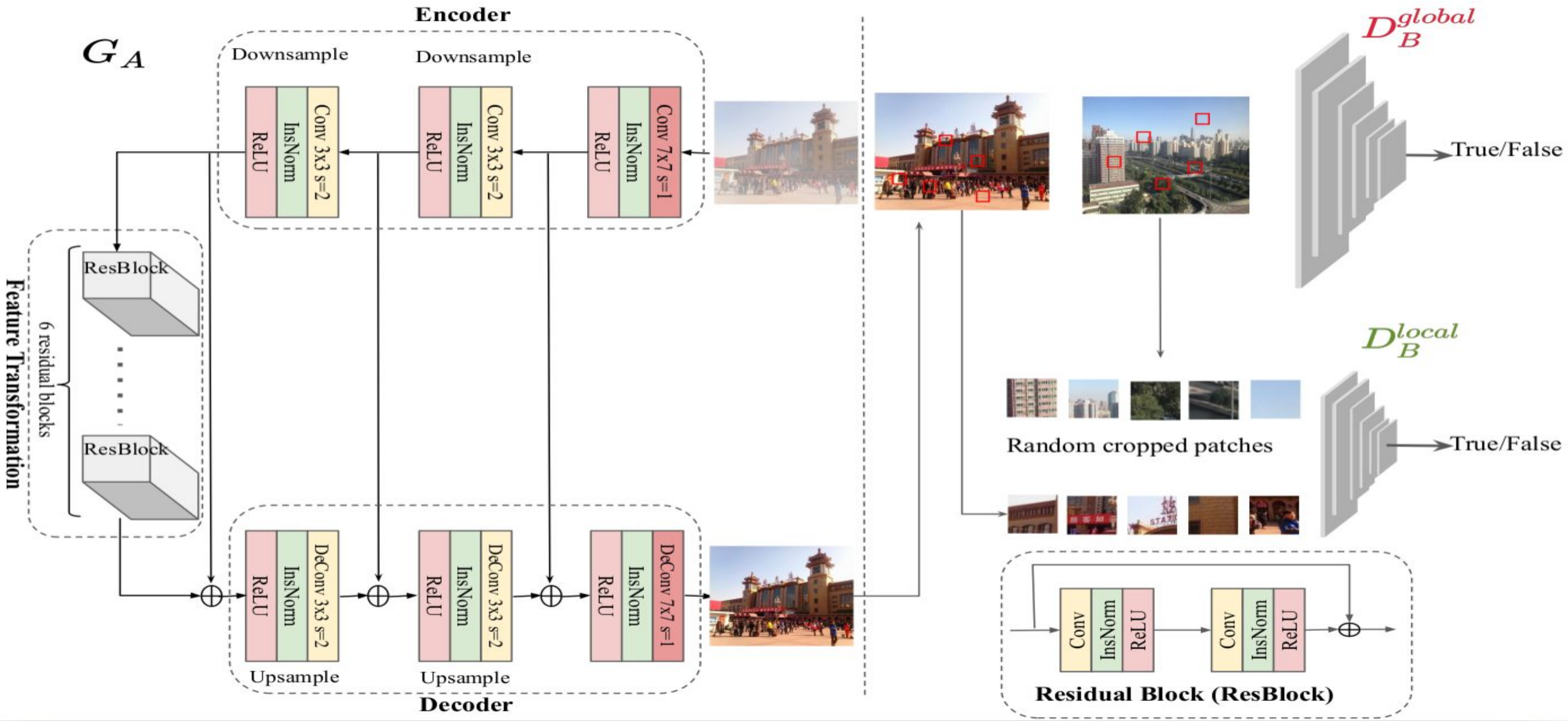


Overview of ECDN

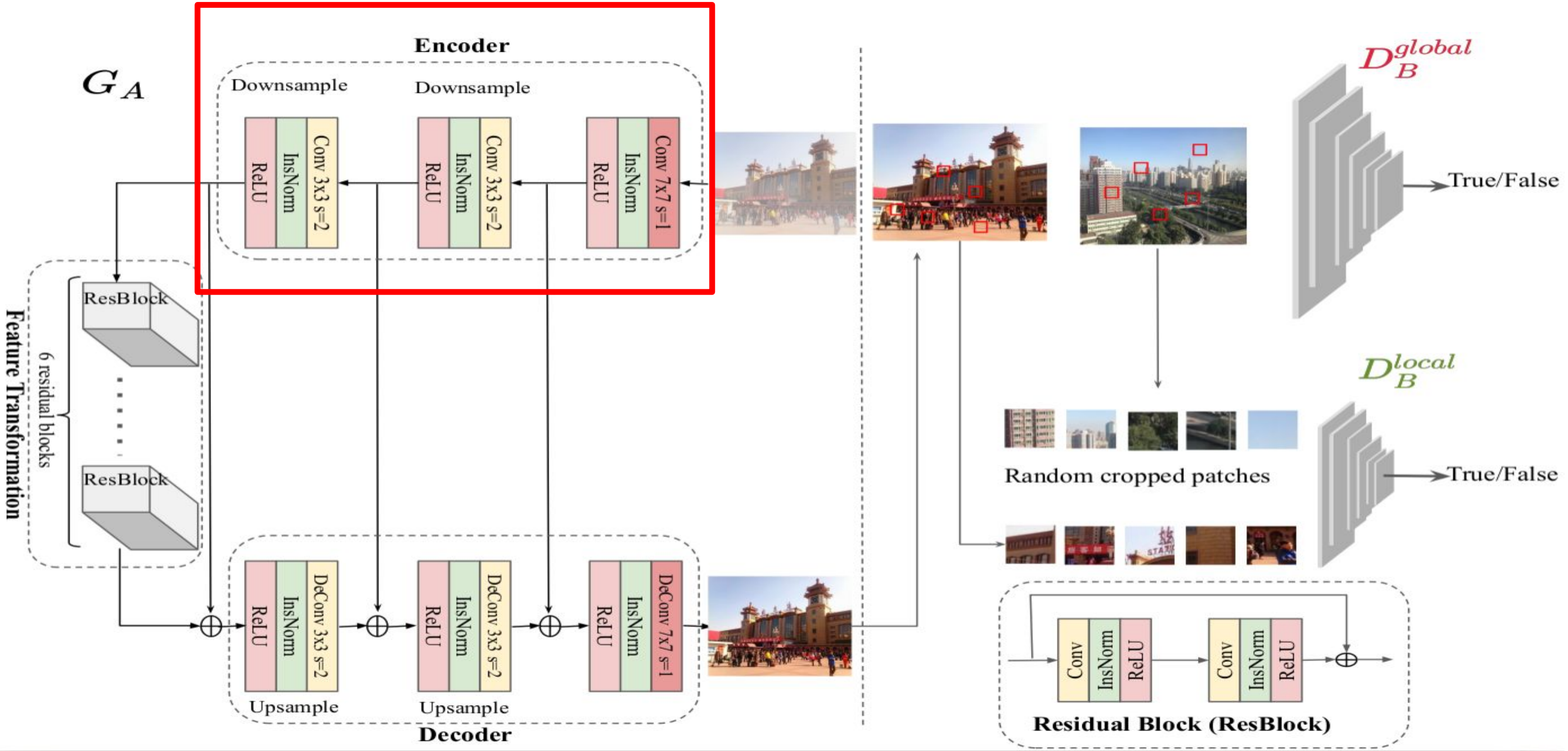
capture the intuition that if we translate from domain **A** to **B** and back, we arrive at where we started



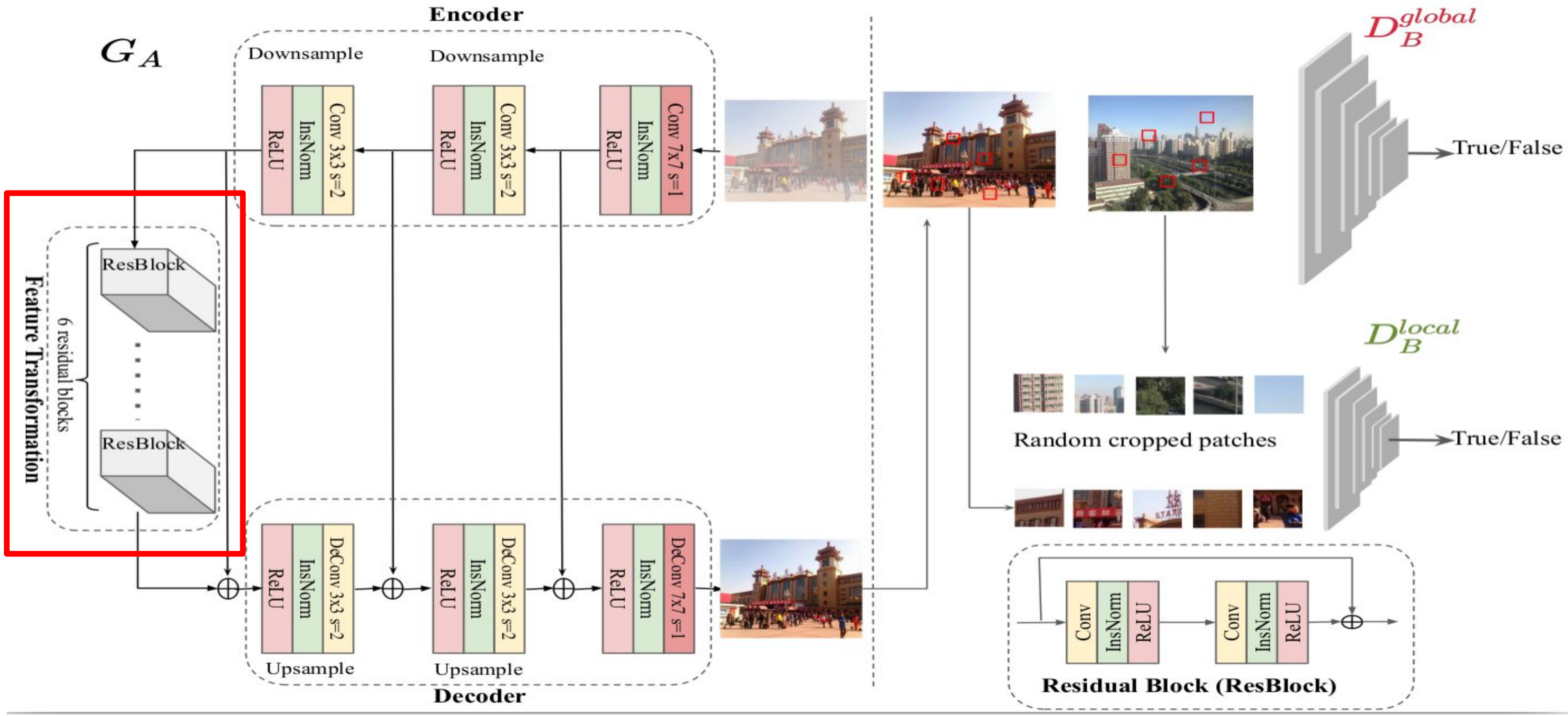
ECDN Architecture



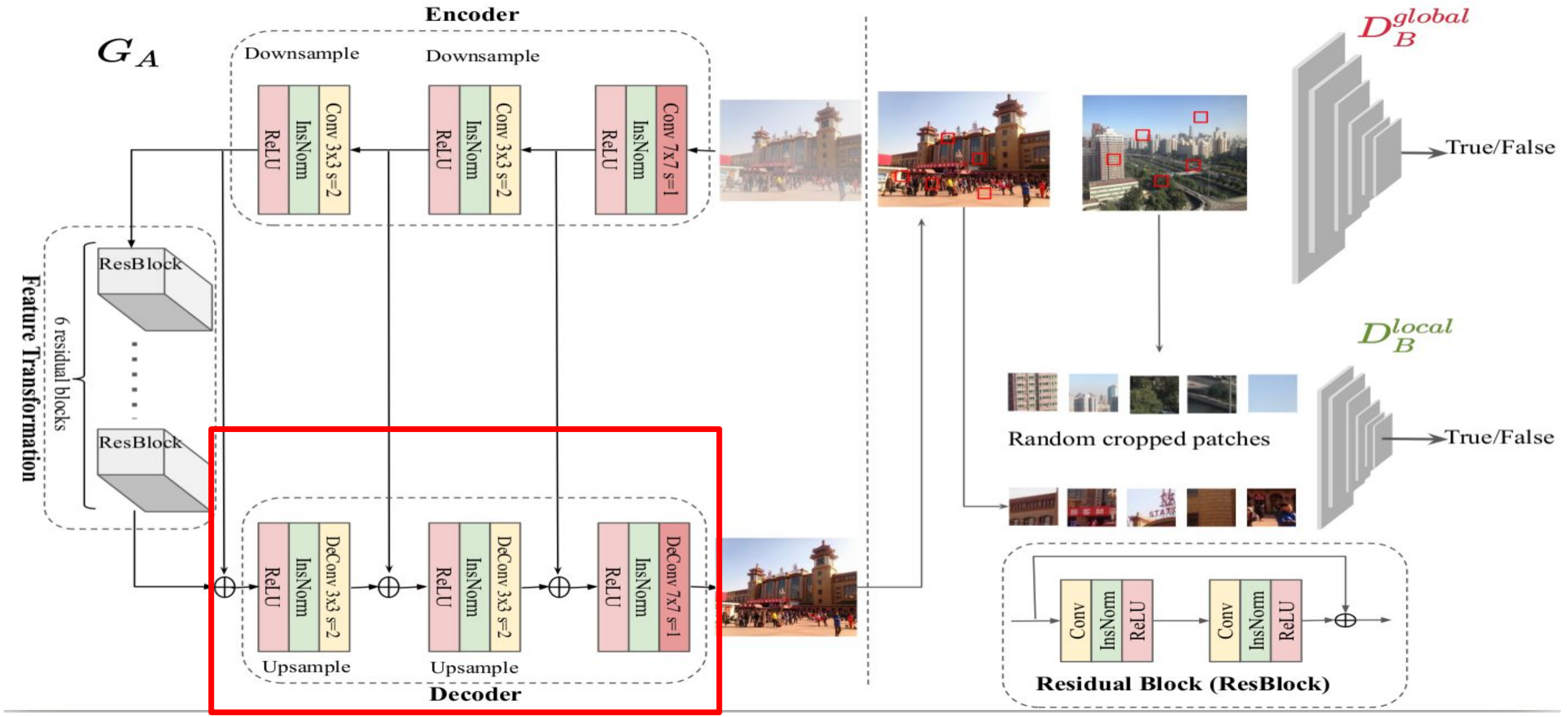
ECDN Architecture



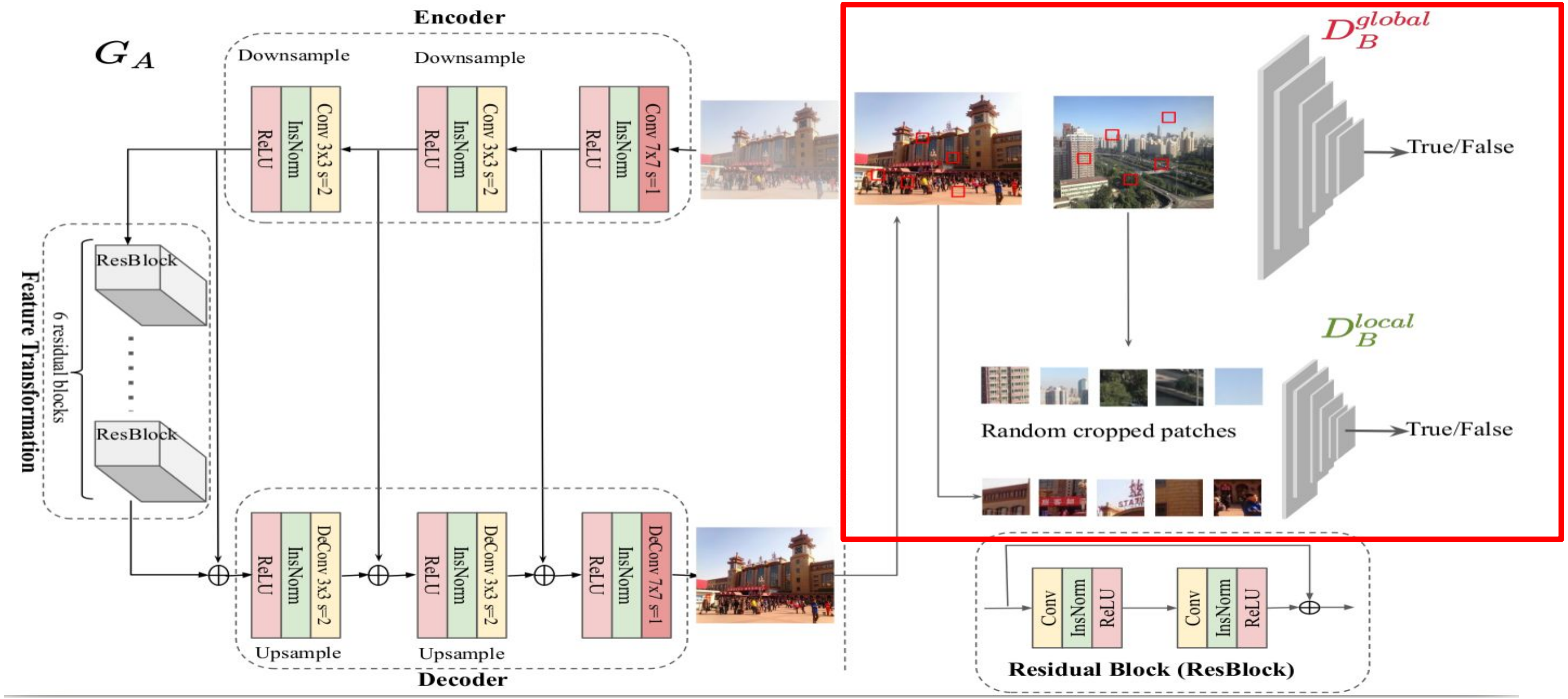
ECDN Architecture



ECDN Architecture



ECDN Architecture



Loss Functions

- Adversarial loss:
  - For matching the distribution of generated images to the data distribution in the target domain
- Cycle consistency loss:
  - to prevent the learned mappings GA and GB from contradicting each other
- Cyclic perceptual loss:
  - to help the generators generate more visually pleasing images
- **We introduced self-regularized color loss:**
  - to avoid color shifting and artifacts in generated haze-free images and also guide the generator to generate images with vibrant colors.

Self-regularized Color Loss

(a) w/o color loss

(b) with color loss

(c) w/o color loss

(d) with color loss

Comparison with CycleGAN Methods

PSNR: 12.14, SSIM: 0.74 | PSNR: 13.43, SSIM: 0.78 | PSNR: 16.10, SSIM: 0.74 | PSNR: 19.11, SSIM: 0.90

(a) Hazy image (b) CycleGAN (c) Cycle-Dehaze (d) Ours (e) Ground truth

Ablation Study

Setting	↑ PSNR	↑SSIM	↓ CIEDE2000
CycleGAN	13.3879	0.5223	17.6113
ECDN w/o color loss	14.5402	0.7407	15.6401
ECDN w/o perceptual loss	14.6582	0.7312	15.6348
EDCN w/o residual blocks	14.1092	0.6923	16.4344
EDCN w/o local discriminator	14.0681	0.7111	19.9466
ECDN	**16.0531**	**0.8244**	**14.9436**

Ablation study over NYU-Depth dataset. The larger values of PSNR, SSIM and the smaller value of CIEDE2000 indicate the better dehazing and perceptual quality

Quantitative Results

Method	↑PSNR	↑SSIM	↓CIEDE2000
DCP (He et al., 2010)	10.9803	0.6458	18.9781
CycleGAN (Cai et al., 2016)	13.3879	0.5223	17.6113
Cycle-Dehaze (Engin et al., 2018)	15.41	0.66	19.04432
DDN (Yang et al., 2018)	15.5456	0.7726	**11.8414**
DehazeNet (Cai et al., 2016)	12.8426	0.7175	15.8782
MSCNN (Ren et al., 2016)	12.2669	0.7000	17.4497
Ours	**16.0531**	**0.8244**	14.9436

Average PSNR, SSIM, and CIECDE2000 results on NYU dataset.

Quantitative Results

Method	↑PSNR	↑SSIM
DCP (He et al., 2010)	12.0234	0.6902
CycleGAN (Cai et al., 2016)	11.3037	0.3367
Cycle-Dehaze (Engin et al., 2018)	15.6016	0.8532
DDN (Yang et al., 2018)	14.9539	0.7741
DehazeNet (Cai et al., 2016)	13.5959	0.7502
MSCNN (Ren et al., 2016)	13.5501	0.7365
Ours	**15.8747**	**0.8601**

Average PSNR and SSIM results on Middlebury dataset.

Qualitative Results

Conclusions

- We proposed a novel dehazing network, called ECDN
- Through ablation study, we showed the effectiveness of local-global discriminators as well as self-regularized color loss and perceptual loss
- Through extensive analysis, we showed that ECDN outperforms previous work

Thank You for Listening!

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