# Paper Reading Group

vision@ouc
Li Na

CVPR 2017

2017.7.22

# Articles List

1.Fast Haze Removal for Nighttime Image Using Maximum Reflectance Prior

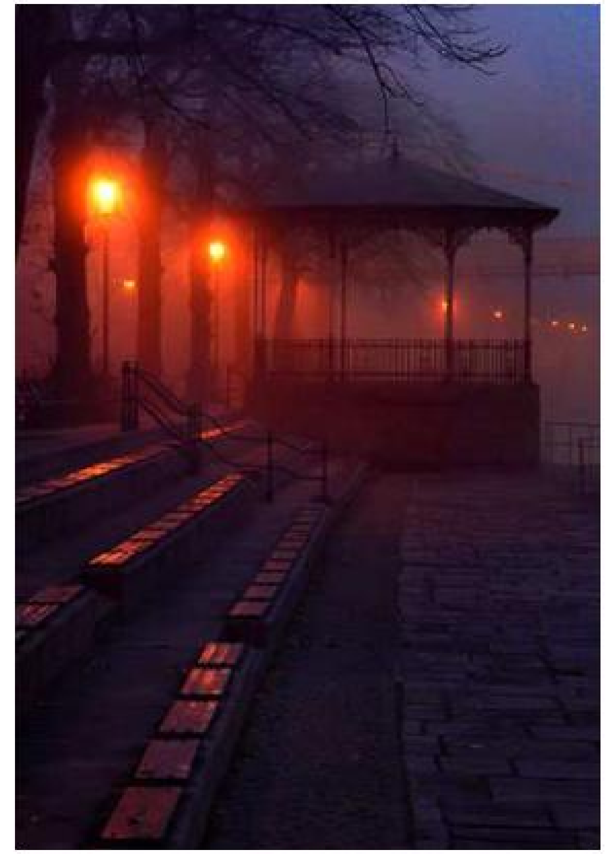
2.WaterGAN: Unsupervised Generative Network to Enable Real-time Color Correction of Monocular Underwater Images

# Title and Authors

## Fast Haze Removal for Nighttime Image Using Maximum Reflectance Prior

Jing Zhang,
Yang Cao,
University of Science and Technology of China Hefei






# Abstract


Propose a simple but effective image prior, **maximum reflectance prior** to estimate the varying ambient illumination.

For the nighttime haze image, **the local maximum intensities** at each color channel are mainly contributed by the ambient illumination.

# Introduction

The hazy images suffer from significant visibility degradation:

- the attenuation of the direct reflection light
- the accumulation of the scattering ambient light.

Daytime hazy imaging model and priors do not hold for most nighttime hazy scenes.

- assume the ambient illumination is globally consistent.
- estimate a white ambient light from the brightest region in the image.

- # The goal:

- Estimate the ambient illumination and the atmospheric transmission for each pixel

- the nighttime hazy imaging model
  - the direct attenuation term
  - the scattering term
    - varicolored ambient illumination
    - non-uniform ambient illumination

- The haze model:

$$I_i^{\lambda} = J_i^{\lambda} t_i + A^{\lambda}(1 - t_i)$$

$$I_i^{\lambda} = A^{\lambda} R_i^{\lambda} t_i + A^{\lambda}(1 - t_i) \overset{\Delta}{=} L_i \eta_i^{\lambda} R_i^{\lambda} t_i + A^{\lambda}(1 - t_i)$$

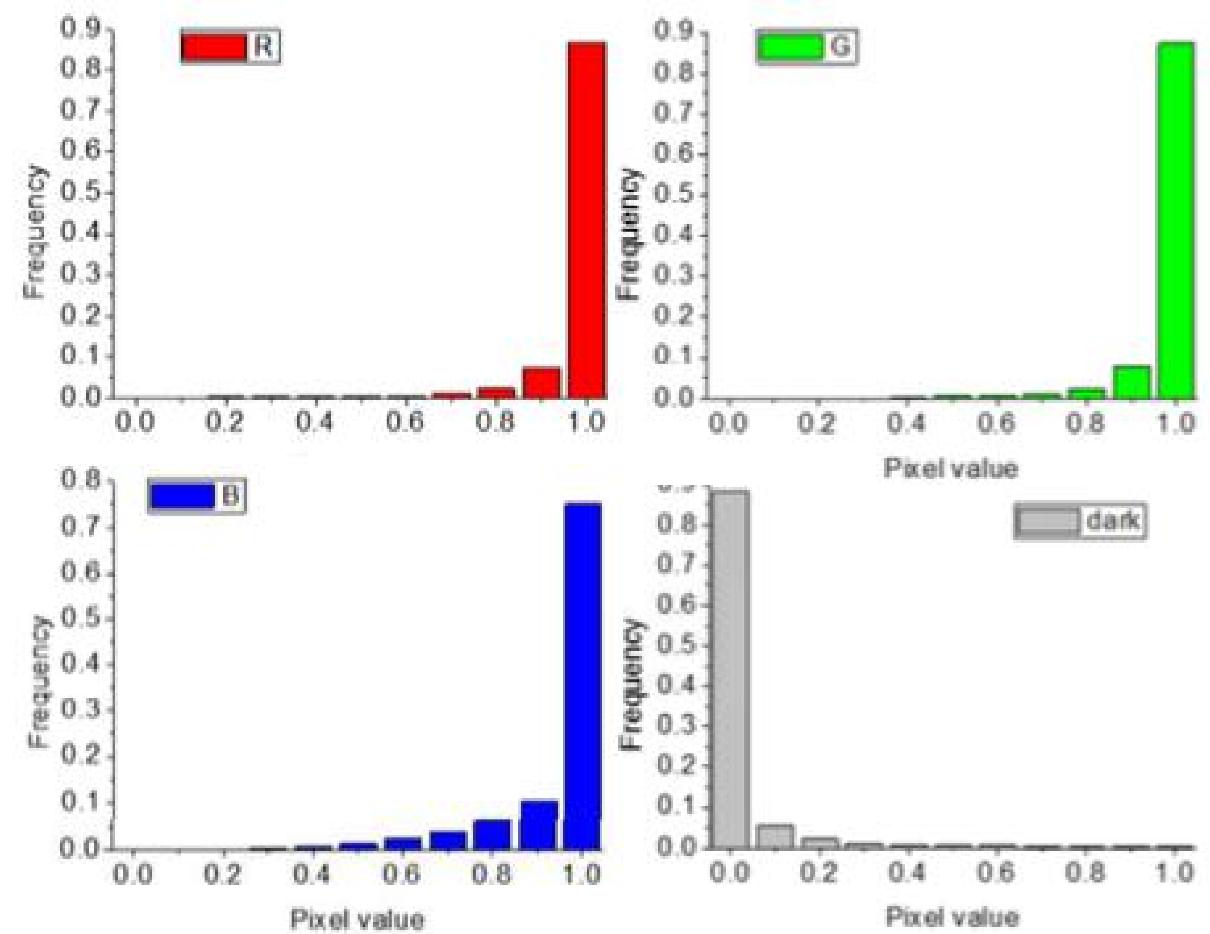
# Nighttime image dehazing

- Estimation of ambient illumination
- Haze removal
- A Faster Approximated Estimation Method

# Maximum reflectance prior

- Maximum reflectance map and Estimation of ambient illumination

$$M_{\Omega_i}^{\lambda} = \max_{j \in \Omega_i} I_j^{\lambda} = \max_{j \in \Omega_i} L_j R_j^{\lambda}$$



# Maximum reflectance prior

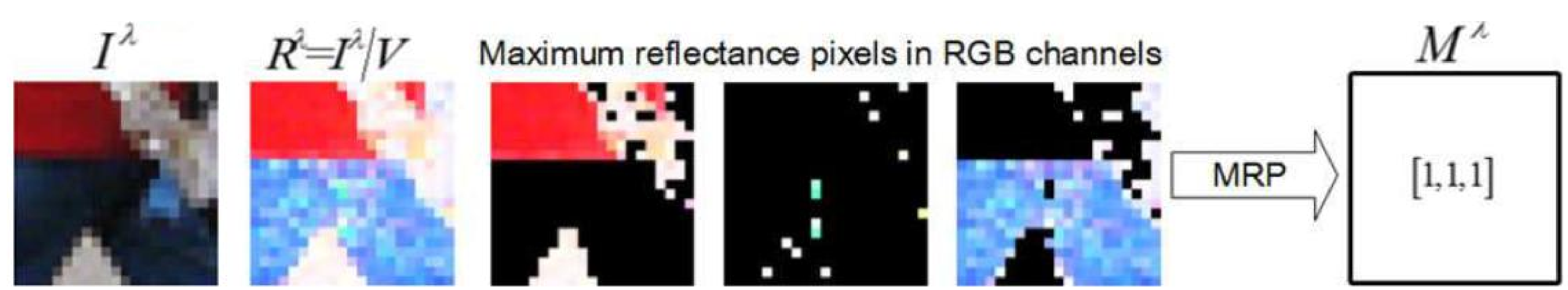
- Maximum reflectance map and Estimation of ambient illumination

$$M_{\Omega_i}^{\lambda} = \max_{j \in \Omega_i} I_j^{\lambda} = \max_{j \in \Omega_i} L_j R_j^{\lambda}$$

$$I_i^{\lambda} = A^{\lambda} R_i^{\lambda} t_i + A^{\lambda}(1 - t_i) \overset{\Delta}{=} L_i \eta_i^{\lambda} R_i^{\lambda} t_i + A^{\lambda}(1 - t_i)$$

$$M_{\Omega_i}^{\lambda} = \max_{j \in \Omega_i} I_j^{\lambda} = \max_{j \in \Omega_i} (L_i \eta_i^{\lambda} R_i^{\lambda} t_i + L_i \eta_i^{\lambda}(1 - t_i)) = L_i \eta_i^{\lambda}$$

$$\eta_{\Omega i}^{\lambda} = \frac{M_{\Omega_i}^{\lambda}}{L_{\Omega_i}}$$



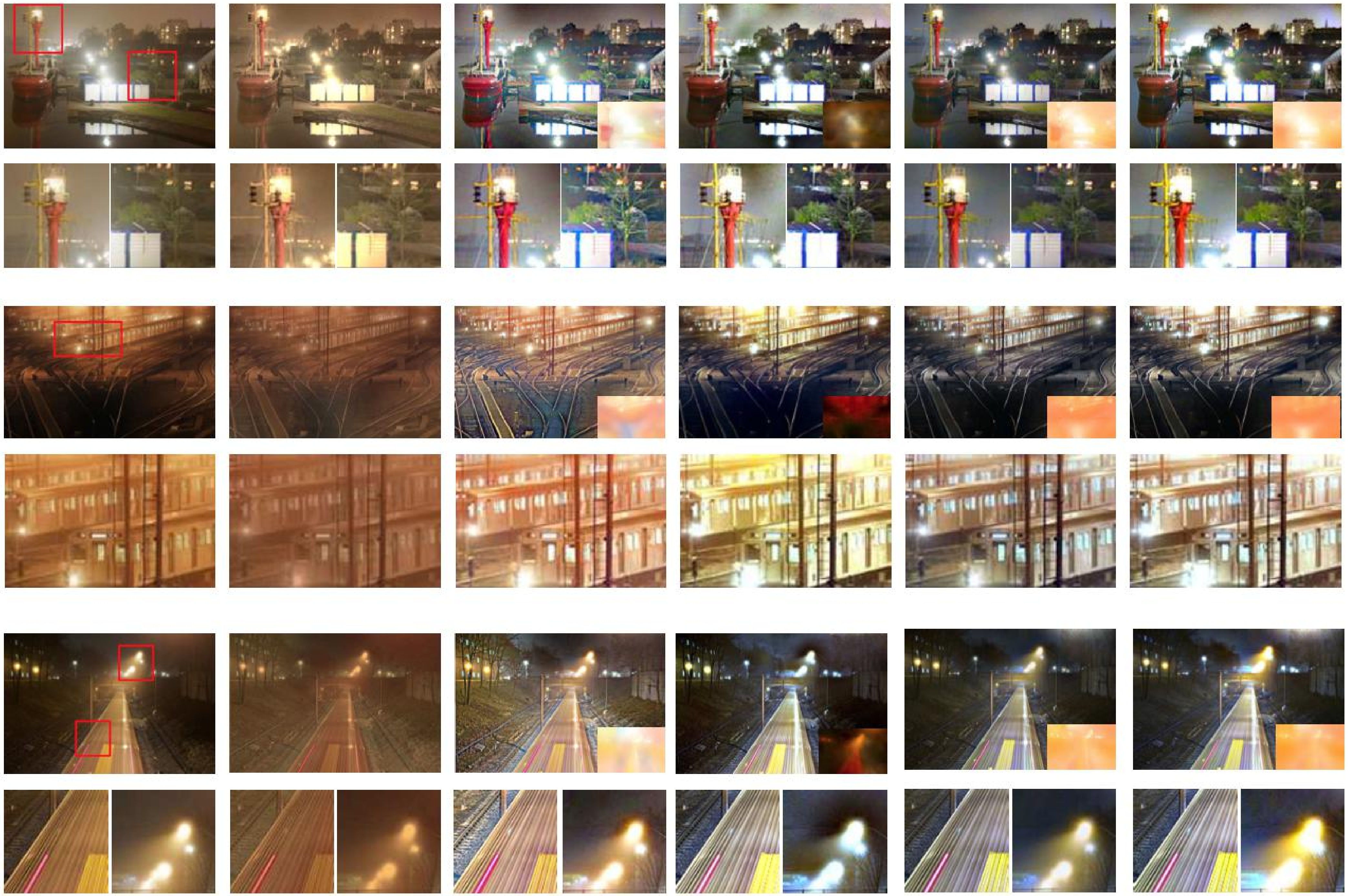
# Haze removal

$$\hat{I}_j^\lambda \overset{\Delta}{=} \frac{I_j^\lambda}{\eta_\mathrm{j}^\lambda}$$

$$L_{\Omega_i} = \max_{\mathrm{j} \in \Omega_\mathrm{i}} \hat{I}_j^\lambda$$

$$t_{\Omega_i} = 1 - \min_{j \in \Omega_i} I_j^\lambda$$

$$J_j^\lambda = \frac{I_j^\lambda - L_j}{\max(t_j, t_0)} + L_j$$



(a) (b) (c) (d) (e) (f)

# Experimental results and discussion

- Results on intermediate hazy image estimation
- Qualitative comparisons on real images
- Quantitative comparisons on synthesized images
- Runtime evaluation

Table 1. PSNR and SSIM for the dehazing results on synthetic hazy images.

| | PSNR | SSIM |
|---|---|---|
| Hazy image | 13.89 | 0.9938 |
| Zhang et al. | 15.99 | 0.9962 |
| Li et al. | 15.74 | 0.9958 |
| MRP | **16.88** | **0.9966** |
| MRP_Faster | 14.43 | 0.9950 |

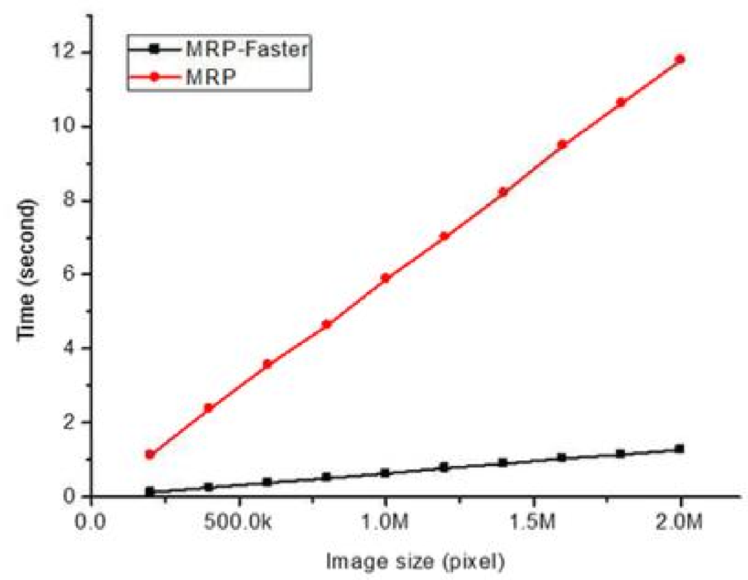
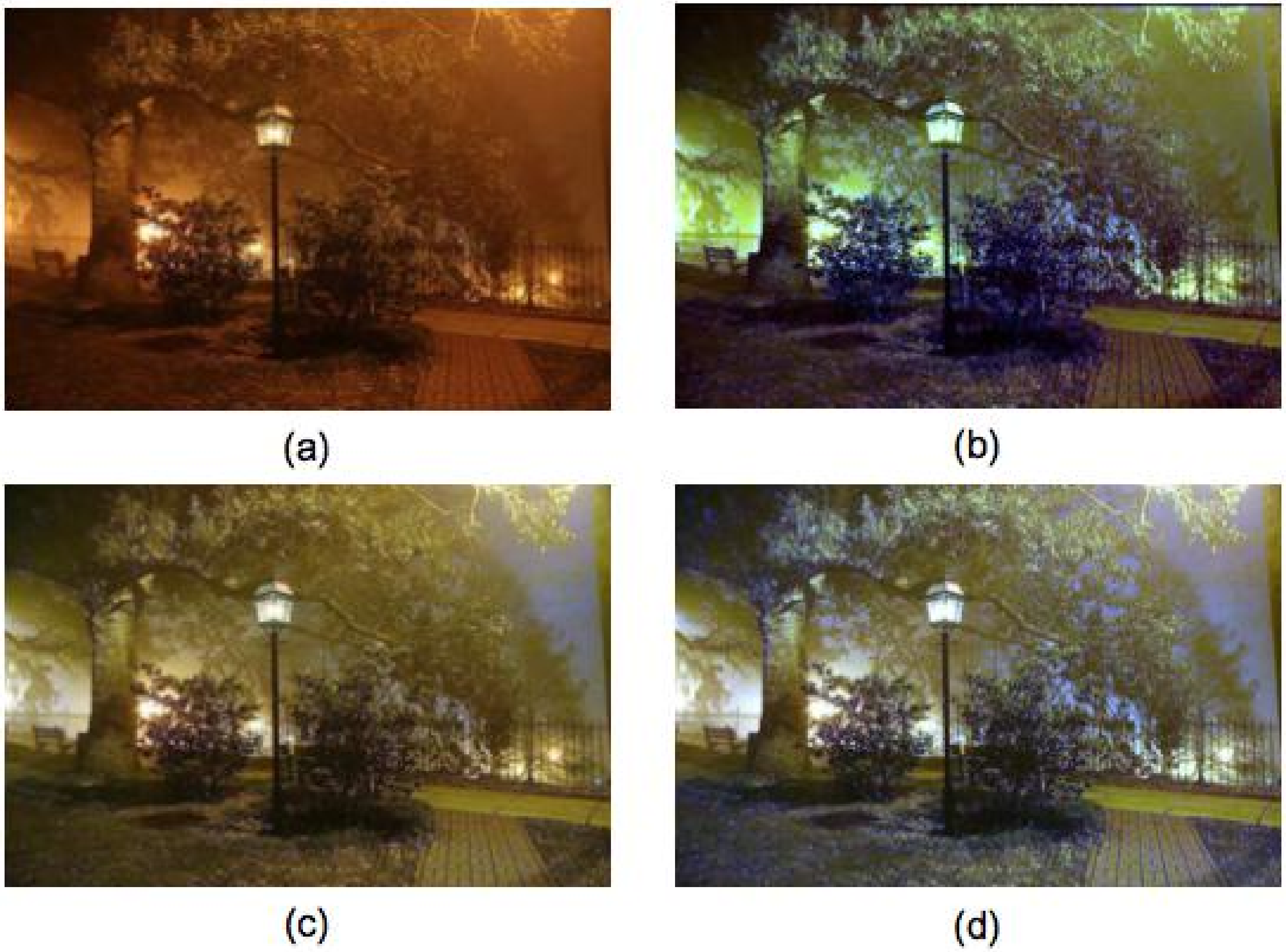



Figure 8. Runtime evaluation of the proposed MRF and MRF-Faster approaches.

# Discussion and Conclusion

- When the scene objects are inherently with solely distinct color, the maximum reflectance prior becomes invalid.
- The proposed scheme will generate color distortions for these objects, such as the grasses and leaves in Fig.



# Title and Authors

WaterGAN: Unsupervised Generative Network to Enable Real-time Color Correction of Monocular Underwater Images

Jie Li,
Katherine A. Skinner,
Ryan M, Eustice
Matthew Johnson-Roberson

# Abstract

- Using WaterGAN, we generate a large training dataset of paired imagery, both raw underwater and true color in-air, as well as depth data.
- This data serves as input to a novel end-to-end network for color correction of monocular underwater images.
- The end-to-end network implicitly learns a coarse depth estimate of the underwater scene from monocular underwater images.

# Technical approach

## Two-part:

- Generating Realistic Underwater Images
- End-to-end model Learning

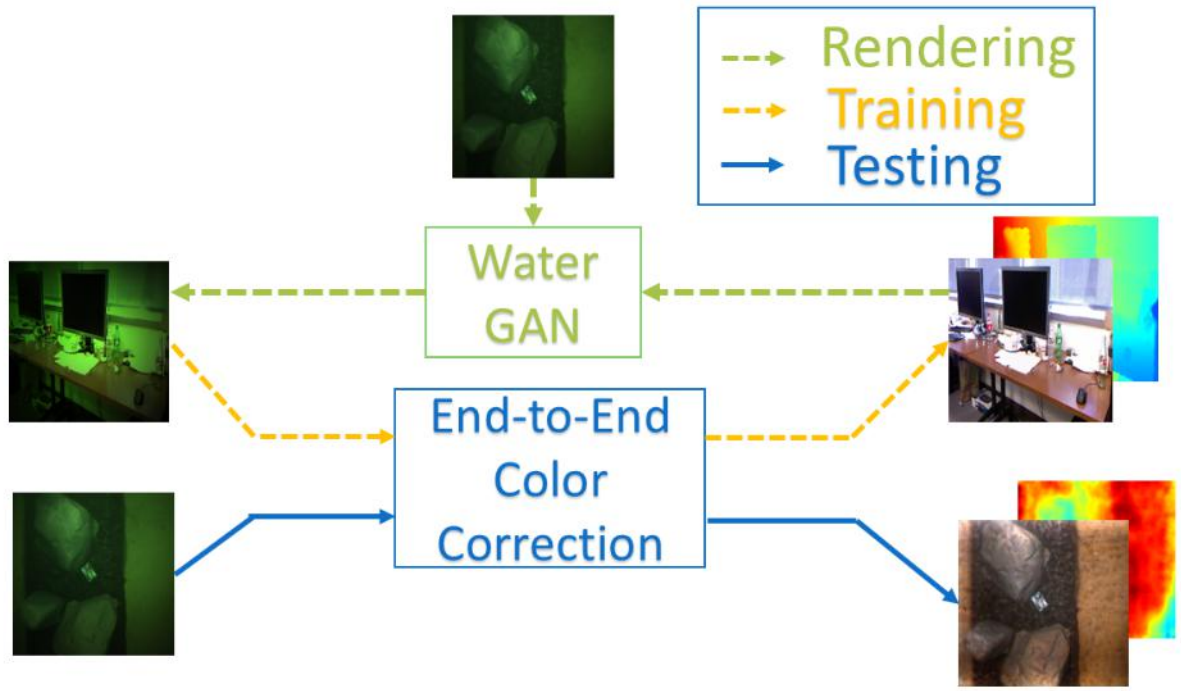



Fig. 1: System flowchart displaying both the GAN network and the end-to-end color correction network proposed.

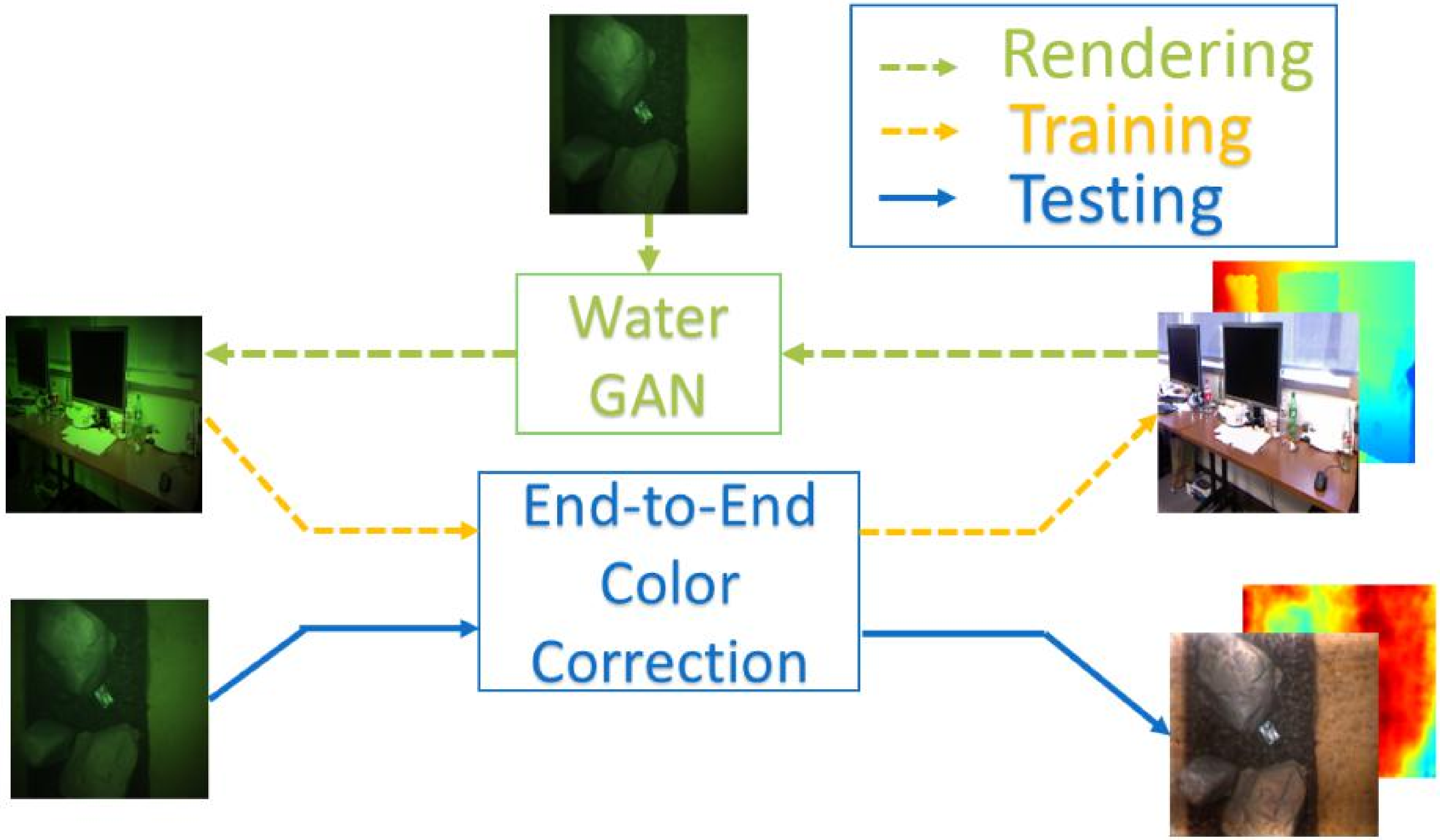



Fig. 1: System flowchart displaying both the GAN network and the end-to-end color correction network proposed.

$$\log(D(x)) + \log(1 - D(G(z)))$$

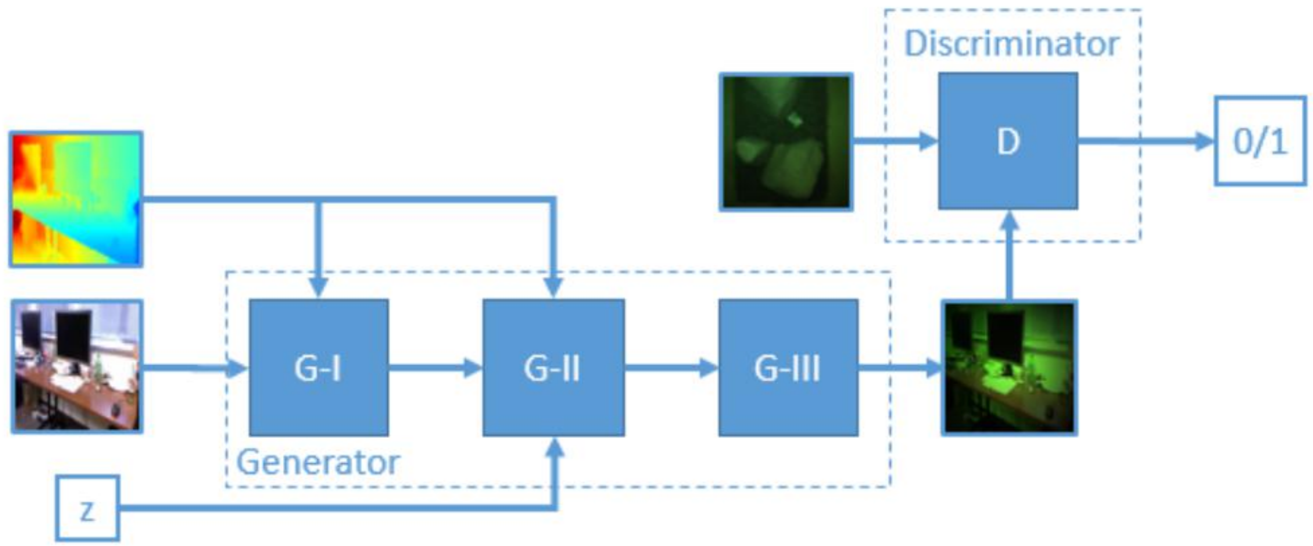



Fig. 2: WaterGAN: The GAN for generating water column attenuated images with similar image formation properties to those of unlabeled underwater data taken in the field.

Two networks training:
- a generator G
  a discriminator, D

Three main stages:
- attenuation(G-1)
- scattering(G-2)
- vignetting(G-3)

Input: **RGB-D**
and alter the **color** and **intensity**
**not** alter the **structure** or **texture**

$$\log(D(x)) + \log(1 - D(G(I_{\text{air}}, r_c, z)))$$

G-I: Attenuation

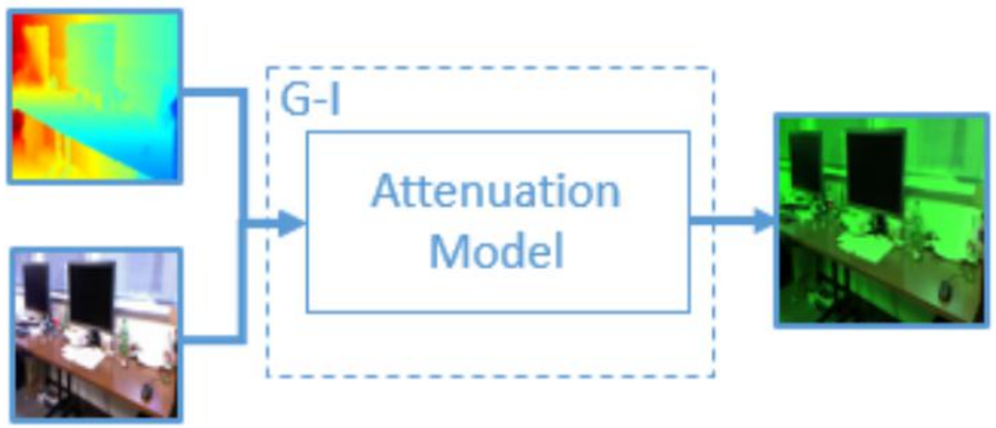



Fig. 3: Generator: attenuation layers

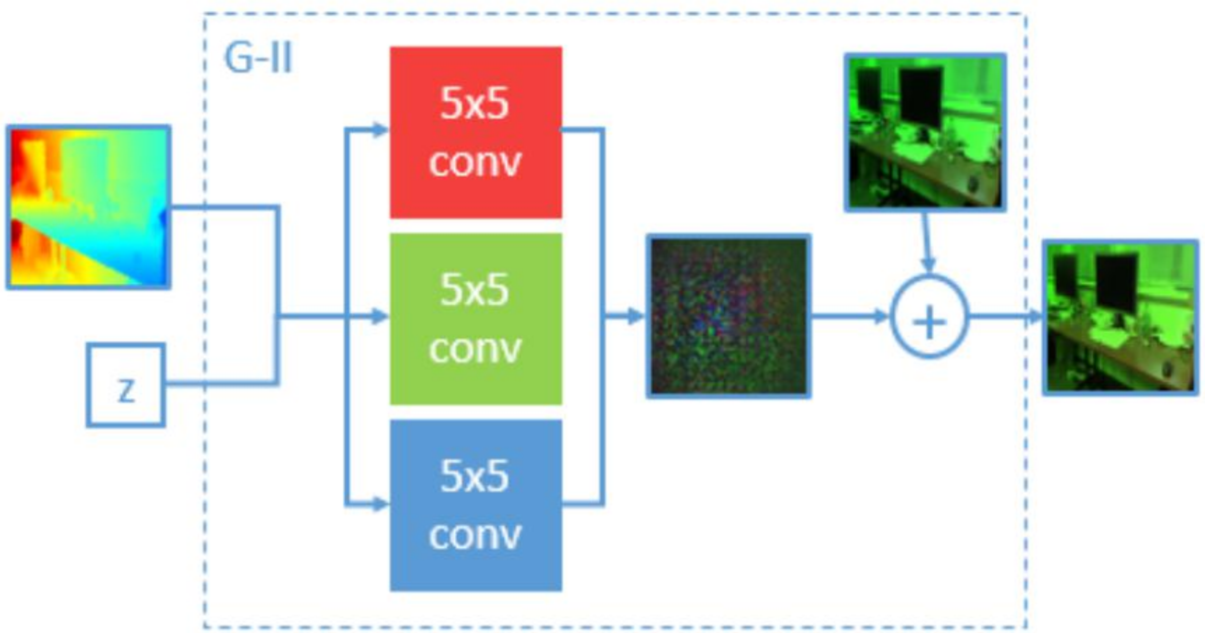



Fig. 4: Generator: scattering layers

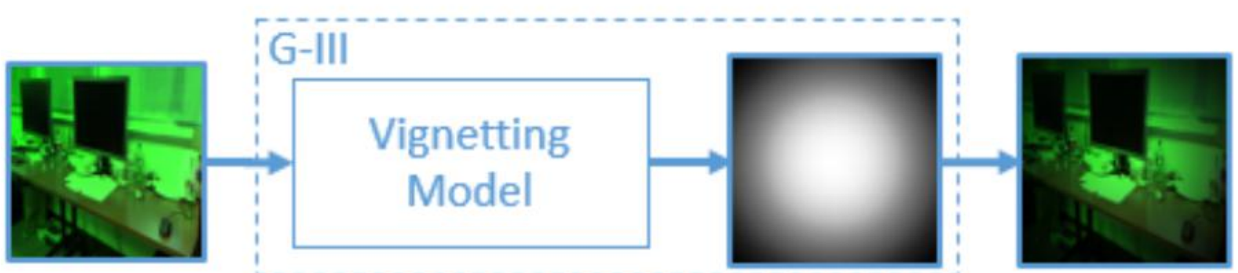



Fig. 5: Generator: vignetting layers

Range-dependent attenuation of light
Jaffe-McGlamery model

$$G_1 = I_{air} e^{-\eta(\lambda) r_c}$$

Backward scattering
a characteristic haze effect model:

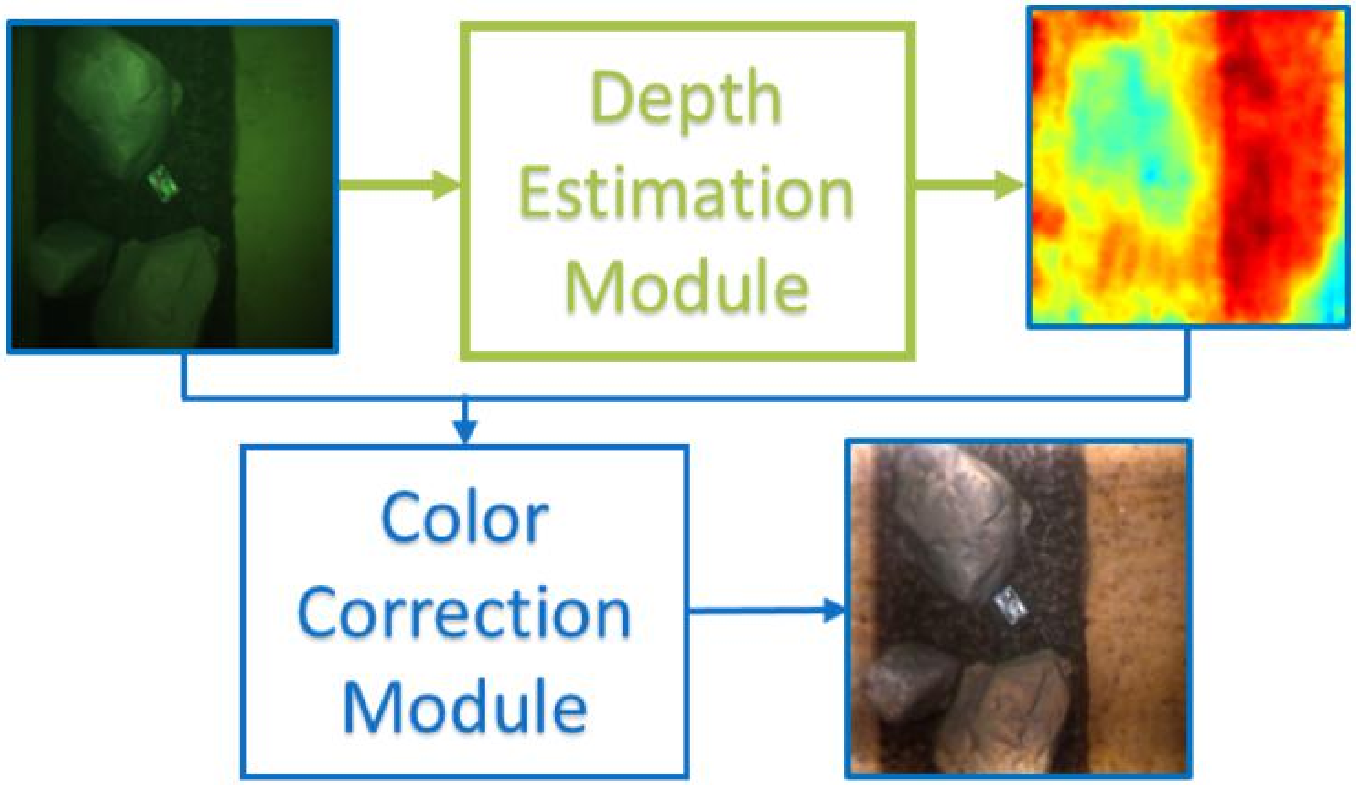
$$B(\lambda) = \beta(\lambda)(1 - e^{-\eta(\lambda) r_c})$$

$$G_2 = G_1 + M_2$$

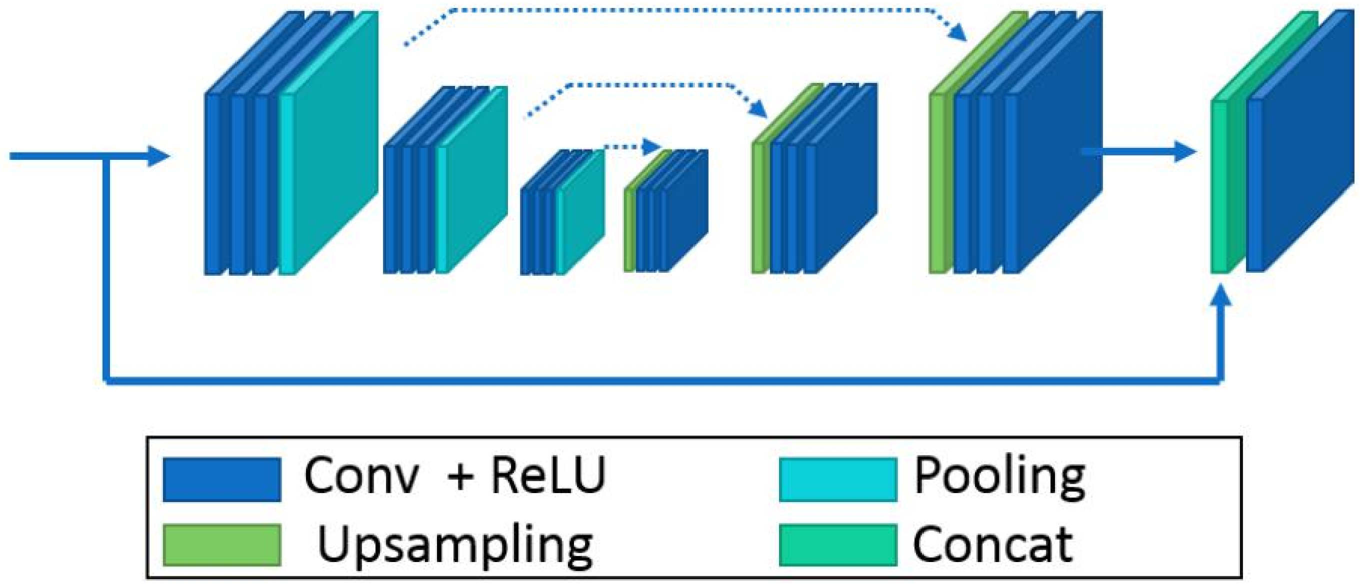
Vignetting model
a shading pattern around the borders of
an image due to effects from lens

$$M_3 = A \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

$$G_3 = M_3 G_2$$




Module1 :
estimates depth from underwater images using the information encoded in attenuation.
Module2 :
takes that estimated depth and inverts the underwater image formation process.




- A state-of-the-art fully convolutional encoder-decoder network for end-to-end dense learning.

The encoder network consists of 9 convolution layers followed by ReLU and 3 max-pooling layers for downsampling.

The decoder use the upsample layers.

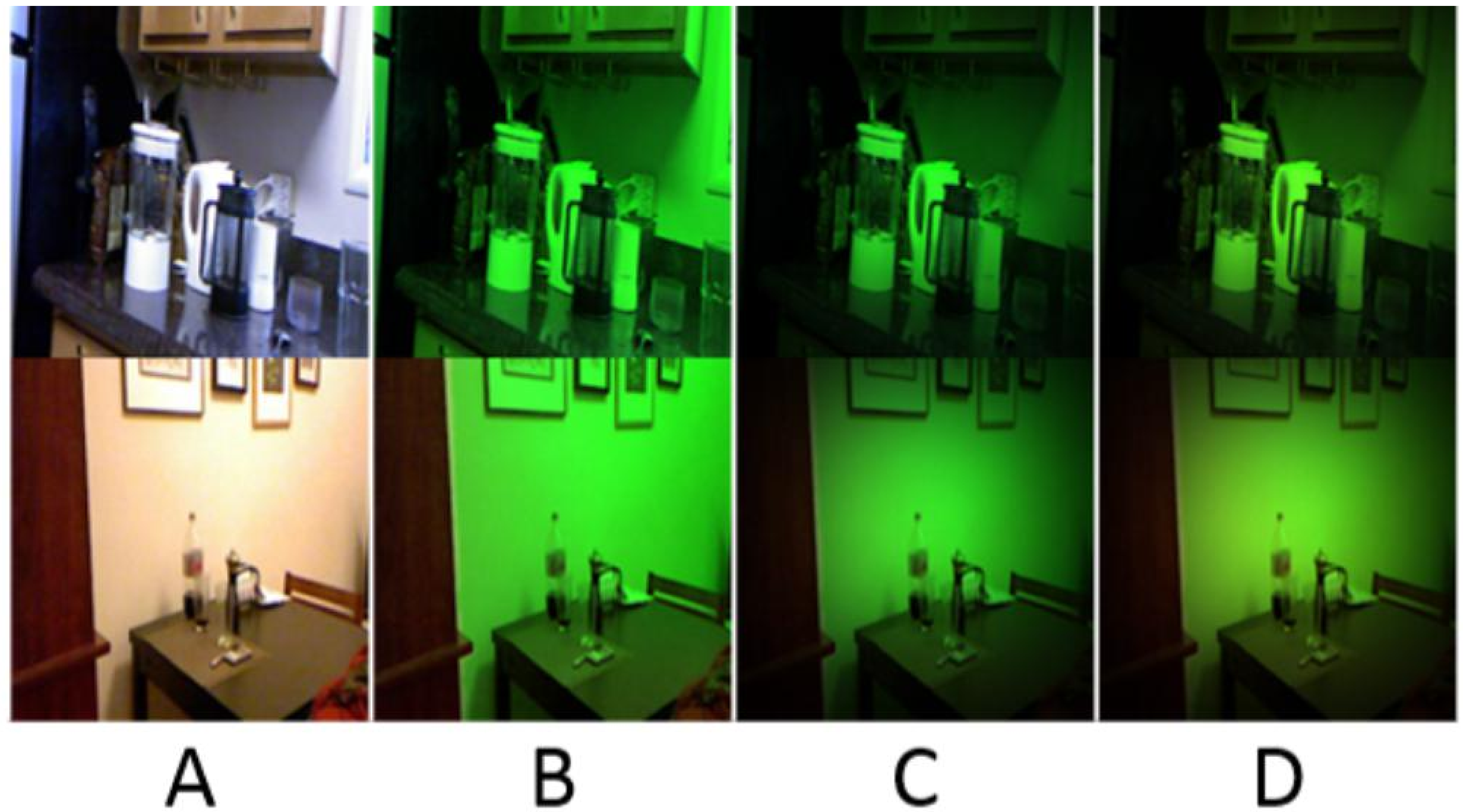
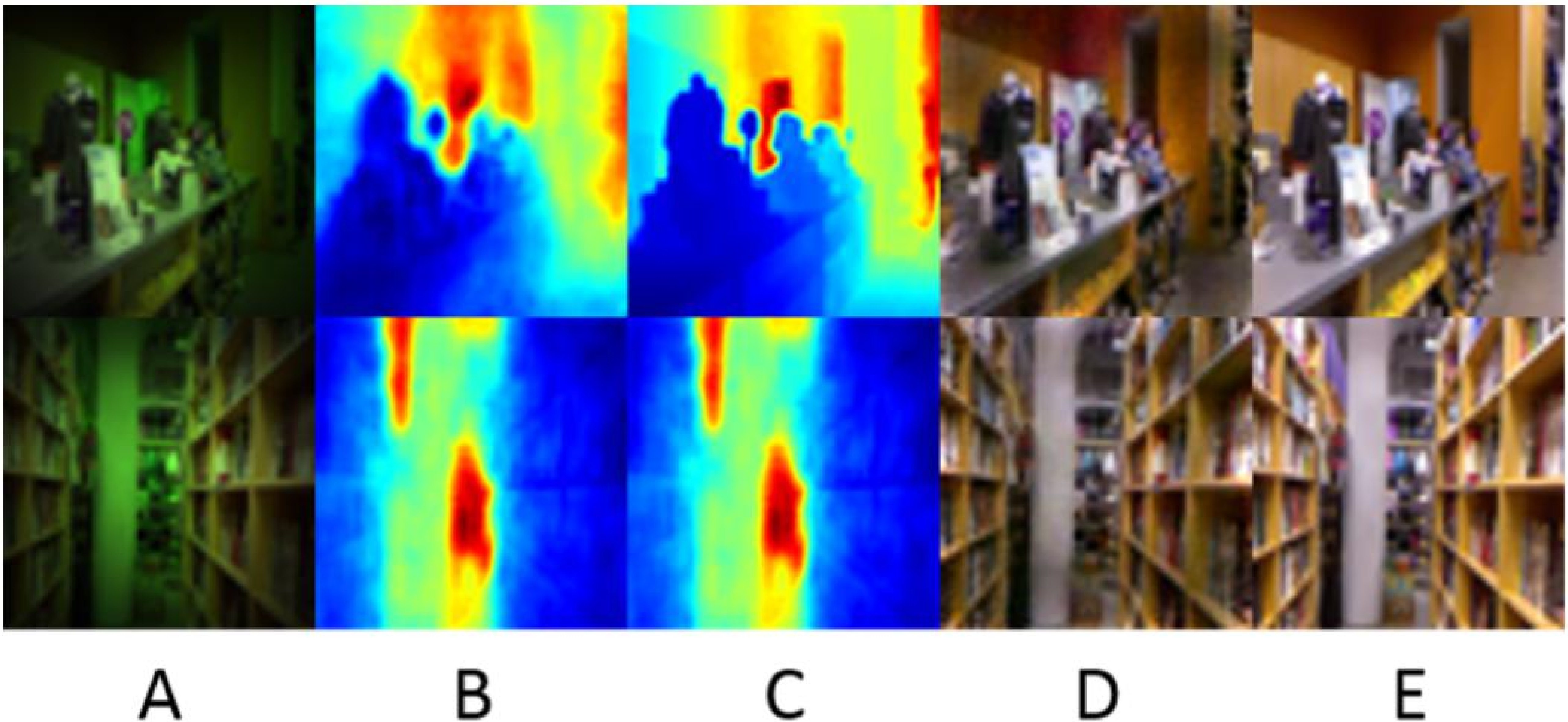



Fig. 9: Air images rendered using the generator trained on as if taken in the MHL tank water column. A is the original image, B is with attenuation applied, C with attenuation and vignetting, and D with attenuation, vignetting, and scattering.

# Result



# Discussion

We would like to experiment with adding additional layers to this stage for capturing more complex effects, such as lighting patterns from sunlight in shallow water surveys.

Thank you