# NTIRE2019 dehazing challenge factsheet RI-GAN: An End-to-End Network for Single Image Haze Removal

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## 1 Team details

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- **Affiliation of the team and/or team members with NTIRE2019 sponsors**: Null
- **User names and entries on the NTIRE2019 Codalab competitions (development/validation and testing phases)**: Development phase (Entries)–akshay.aad16 (31); Testing phase (Entries)–akshay.aad16 (4)
- **Best scoring entries of the team during development/validation phase**: Entry–$24^{th}$; Score–PSNR:16.31 and SSIM:0.470389; Rank–$14^{th}$
- **Link to the codes/executables of the solution(s)**: Attached to the mail

# 2 Contribution details

**Title:– RI-GAN: An End-to-End Network for Single Image Haze Removal**

## 2.1 General method description

An end-to-end network is proposed to recover the haze-free scene from hazy scene. Proposed network is trained adversarially to learn the haze related features. We propose a novel Residual-Inception (RI) module which comprises of advantages of both residual [1] and inception block [2]. Proposed RI-module can be extended for the feature extraction in various computer vision tasks such as semantic segmentation, depth estimation, object recognition etc.

## 2.2 Solution for Single Image De-hazing

Outdoor scene images generally undergo visibility degradation in the presence of aerosol particles such as haze, fog, and smoke. Most of the initial approaches estimate the scene transmission map, airlight component and make use of an atmospheric scattering model to recover the haze-free scene. In spite of the remarkable progress of these approaches, they propagate cascaded error upstretched due to the employed priors. We embrace this observation and designed an end-to-end generative adversarial network (GAN) for single image haze removal. Proposed network bypasses the intermediate stages and directly recovers the haze-free scene. Generator architecture of the proposed network is designed using novel residual inception (RI) module. Proposed RI module comprises of dense connections within the multi-scale convolution layers which allows it to learn the integrated flavors of the haze-related features. Also, we propose a dense residual module for discriminator network of RI-GAN. Further, to preserve the edge and the structural details in the recovered haze-free scene, structural consistency loss [3] and edge consistency loss along with the L1 loss are incorporated in proposed RI-GAN. Experimental analysis has been carried out on NTIRE 2019 [4], D-Hazy [5] and indoor SOTS databases [6]. Experiments on benchmark datasets show that the proposed network outperforms the existing state-of-the-art methods for single image haze removal.

## 2.3 List of the Contributions

The key contributions of this work are listed below:

1. An end-to-end generative adversarial de-hazing architecture is proposed to minimize the errors upstretched in prior-based approaches.
2. A novel generator network which comprises residual and inception principles in dense connections is proposed.
3. A novel discriminator network is designed using residual principles.
4. A combination of structural consistancy loss and edge consistancy loss is incorporated along with L1 loss to optimize the network parameters.

## 2.4 Representative image / diagram of the method(s)

The proposed approach for single image de-hazing using residual-inception module is shown in Figure 1. Generator architecture comprises of nine residual blocks designed using the proposed residual-inception module which is interlinked using skip connections to share the feature information within themselves. Also, proposed discriminator architecture comprises of dense connections within a residual module which allows the network to discriminate between the fake and real samples robustly.

# 3 Global Method Description

## 3.1 Method Complexity

**Training Phase:** $\approx$ 50 Million parameters.

**Testing Phase:** $\approx$ 46 Million parameters.

## 3.2 Pre-trained Model

Proposed RI-GAN is trained from scratch for single image de-hazing. We have not used any pre-trained model to initialize the proposed RI-GAN.

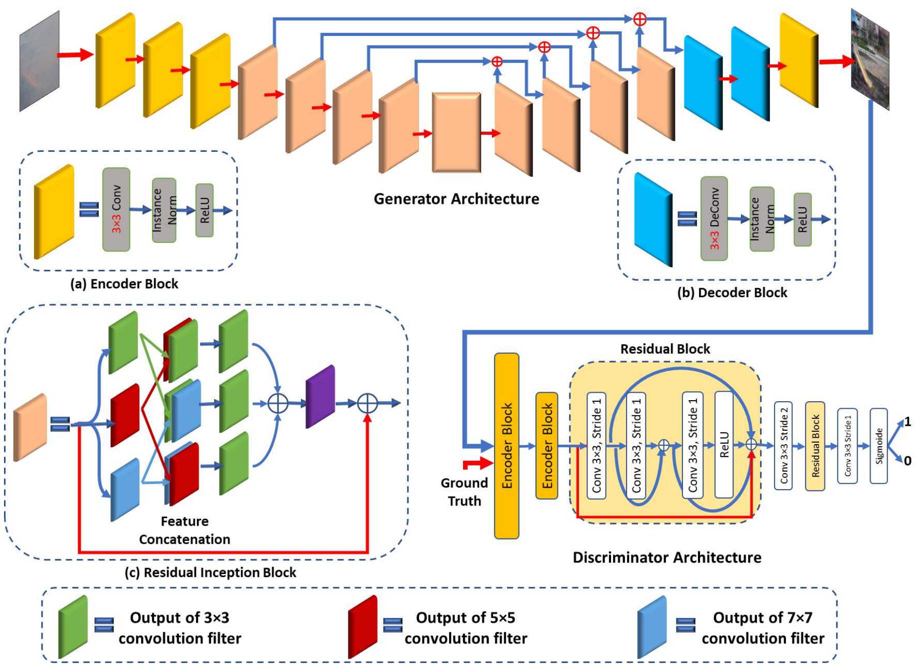


Figure 1: Flow of the proposed approach for single image haze removal.

### 3.3 Training Description

We share a similar approach proposed by [7] for the training of the proposed RI-GAN. Training dataset comprises of indoor (synthetic) and outdoor (real) hazy images. To generate synthetic images, we consider NYU depth [8] dataset. Indoor hazy images (`100`) are synthetically generated using procedure given in [9] with $\beta = 0.8, 1.6$ and `airlight` $(A) = [1,\ 1,\ 1]$. Outdoor hazy and haze-free images are collected from the NTIRE2018 (`35`), NTIRE2019 (`45`) training set. Combinely, `100` synthetic hazy images generated from NYU depth database and `80` outdoor hazy from NTIRE database are used to train the proposed RI-GAN. Remaining settings of the model are similar to the [7]. Weight parameters of network are updated in `200` epochs on PC with 4.20 GHz Intel Core i7 processor and NVIDIA GTX 1080 8GB GPU.

Table 1: Quantitative Analysis of Single Image Haze Removal on NTIRE2019 [4] Database.

| Approach | SSIM | PSNR | CIEDE2000 |
|---|---|---|---|
| **DChP [11]** | 0.2509 | 12.2804 | 22.6058 |
| **CAP [12]** | 0.2653 | 12.1202 | 21.0226 |
| **Proposed Method** | **0.4700** | **16.3100** | **13.3428** |

### 3.4 Testing Description

Irrespective of the input size of the hazy image, it is resized to 500×500 spatial size and feed to the proposed RI-GAN. We process input of 500×500 through proposed RI-GAN to recover the haze-free scene followed by bicubic interpolation to meet the desired dimensions.

### 3.5 Quantitative and qualitative advantages of the proposed solution

Proposed RI-GAN has been analyzed both qualitatively and quantitatively using SSIM [3], PSNR and CIEDE2000 [10] evaluation parameters. For quantitative analysis, proposed RI-GAN is compared with existing dark channel prior (DChP) [11] and color attenuation prior (CAP) [12] on NTIRE2019 validation set. Comparison is shown in Table 1. Qualitative analysis is given in NTIRE2019 workshop manuscript.

### 3.6 Results of the comparison to the other approaches

Comparison with other existing approaches is given in Table 1 on validation set of NTIRE2019 challenge dataset.

### 3.7 Results on other standard bemchmarks

Along with NTIRE2019 challenge dataset, proposed RI-GAN is compared with extising state-of-the-art methods on two benchmark datasets namely, D-Hazy [5], and indoor SOTS [6]. Comparison is given in the manuscript submitted to the NTIRE workshop. This is the cross dataset comparison, because there is no overlap between training and testing images considered for evaluation.

### 3.8 Novelty degree of the solution

Proposed residual-inception (RI) module is a novel approach to extract the features from an input image. Desinged RI-GAN for single image de-hazing is novel contribution and has not been published anywhere.

## 4 Ensembles and fusion strategies

Proposed RI-GAN is an end-to-end network for single image haze removal. Most of the initial approaches estimate the scene transmission map, airlight component and make use of an atmospheric scattering model to recover the haze-free scene. In spite of the remarkable progress of these approaches, they propagate cascaded error upstretched due to the employed priors. On the other hand, proposed RI-GAN recovers haze-free scene directly from hazy scene and hence minimizes the errors upstretched due to the intermediate maps by prior-based approaches.

## 5 Technical Details

### 5.1 Language and implementation details

Specification of the system are given below:
**Implementation platform**: Windows 10 (x64)
**Programming language**: Python
**Libraries**: Tensorflow, Matplotlib, Numpy, Argparse, Json, Glob, Random, Collections, Math, Time, Cv2.
**Graphics card**: NVIDIA GTX 1080 8 GB

### 5.2 Human efforts required for implementation, training, and validation

Codes/Executables are prepared in a simple and understandable way. The user needs to copy the set of testing hazy images in respective folder (Details are given in README.txt file) and needs to run <python RIGAN.py −−mode test>.

### 5.3 Training/testing time? Runtime at test per image

**Training Time**: Approximately 8 to 10 hours on the system specified above.
**Testing Time**: Approximately 0.95 sec per image on the system specified above.

### 5.4 Robustness of the proposed RI-GAN

Proposed RI-GAN is trained over 180 hazy scenes comprises dense as well as light hazy images of different airlight. Thus, proposed RI-GAN is a robust network for single image haze removal and is tested on cross-dataset also. Improved performance even for cross-dataset proves the robustness of proposed RI-GAN for single image haze removal.

### 5.5 Efficiency of the proposed solution

Currently, proposed solution for single image haze removal is efficient works on images with decent speed. Further, improvement can be done in reducing the computational complexity of the proposed RI-GAN and implement it in a compact form which could reduce the execution time of the proposed approach.

## 6 Other details

### 6.1 Planned submission of a solution(s) description paper at NTIRE2019 workshop

As per the deadline of NTIRE2019 workshop, before $2^{nd}$ April 2019, we are planning to submit the proposed solution for haze removal at NTIRE2019 workshop.

### 6.2 General comments and impressions of the NTIRE2019 challenge

This is a well organized and time bounded dehazing challenge which helps all the researcher working in this field to test their algorithms. I would like to thank the organizers for their hard work to carry all the tasks within time and in a smooth manner.

## 6.3 What do you expect from a new challenge in image restoration and enhancement?

It would be more challenging and interesting to work and design a system for video dehazing and analyzing the effect of haze on high-level tasks such as object detection.

## 6.4 Other comments: encountered difficulties, the fairness of the challenge, proposed subcategories, proposed evaluation method(s), etc.

Initially, it was a very scary moment after seeing the level of haze (dense) in the images. At the same time, it generates an interest in the participants and encourages them to solve the real-world problem.

# References


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