SINGLE IMAGE DEHAZING

Borugadda Charan Raj,
21BCE9583,
Dept. of Computer Science & Engg.,
VIT-AP University.

Kambhampalli Tejasri,
21BCE9588,
Dept. of Computer Science & Engg.,
VIT-AP University.

Arkadu Jahnavi,
21BCE9881,
Dept. of Computer Science & Engg.,
VIT-AP University.

Kumavath Sheshu Naik,
21BCE9982,
Dept. of Computer Science & Engg.,
VIT-AP University.

Abstract ~ Hazy or foggy weather can significantly degrade image quality. The scattering of atmospheric particles reduces contrast, alters colours, and obscures object details, making it difficult for both human and computer vision systems to identify objects accurately. Image de-Hazing, the process of restoring visibility in hazy images, is a rigorous task in computer vision. This work introduces a fresh perspective on addressing this challenge, utilizing deep learning techniques. To fit and validate our approach, we utilize the D-HAZE and NH-HAZE datasets, which provide a diverse range of haze and corresponding haze-free images. Our innovative approach efficiently will remove haze while saving important image details, such as color and texture. We quantitatively and qualitatively showcase the enhanced performance of our technique, significantly enhancing the visual quality of hazy images.

Introduction :

Image de-hazing in computer vision is a complex task that seeks to recover sharp images from blurred ones. Haze, a standard atmospheric phenomenon, degrades image quality by reducing visibility and contrast. To handle this concern, we present a new deep learning method that utilizes the strengths of advanced neural networks. Our approach utilizes a combination of the D-Haze and NH-Haze datasets for training. The D-Haze dataset provides a diverse range of simulated hazy images consists of varying stages of haze density, while NH-Haze dataset offers a more realistic and challenging set of non-homogeneous hazy images. Given a hazy image as input, our model aims to generate a clear, haze-free image as output. By training on a large and diverse dataset, our model learns to effectively approximate the atmospheric scattering coefficient and recover the original radiance field**.** This dataset focuses on realistic haze conditions, providing high-resolution images with varying levels of haze intensity. It is essential for training and evaluating De-Hazing algorithms to ensure they can handle different haze densities and produce clear, dense and very good natural-looking sharp images. This dataset includes non-homogeneous haze,where the haze density varies across different parts of the image.

This variation mimics real-world conditions more closely than uniform haze, presenting a more challenging scenario for de-hazing algorithms and helping to develop more robust de-hazing solutions. Single Image De-Hazing de-hazes the image with hazy like dense and non-homogeneous images. Image de-hazing is the process of restoring a hazy or foggy image to clear or sharp images with fine graded details for the uniform and density varies according to the conditions for increasing visibility.

(a) Hazy Image (b) Hazy Free Image

Fig.1 Contrast between foggy and clear images

The Hazy Image (a) is covered by a thick layer of haze or fog. This significantly reduces visibility, making it difficult to distinguish objects and details. The overall image appears blurry, with reduced contrast and muted colors. By applying the art of neural networks and convolutional neural networks we can get a hazy free image by applying some loss functions and optimizer. The de-hazed image (b), on the other hand, presents a much clearer and more detailed view of the room. The haze has been effectively removed, enhancing visibility and revealing the fine details of objects on the shelves. The colors appear more vibrant and the contrast is significantly improved, making the image more visually appealing.

Related Work

Image de-hazing in computer vision is a complex task that seeks to restore clear images from blurred ones. Recent advancements have utilized deep learning architecture and novel training strategies to attain cutting-edge performance. This section explores relevant research focusing on IDT Net architecture, D-Haze and NH-Haze datasets, drawing inspiration from provided references.

Early de-hazing techniques often relied on manually engineered priors, such as the unpaired data [1], higher order curves and dynamic ranges of diversity [3], haze style transfer [8], d-hazy and sots [6], and physics-based models [7,10,16,19]. While these methods could enhance clarity, They often generates unnatural results, particularly in scenes that have not align with the inherent presumptions of prior knowledge.

After the rise in deep learning, de-hazing methods enhanced with the IDE Net [25] based on enhanced atmospheric scattering, DeHazeNet [26] uses the transmission mapping, FFA Net [27] based on extracting relevant features and fusing them to remove haze and TDN Net [28] effectively handles the multi-scale nature of haze. These approaches harness deep learning capacity directly learn complicated representations of feature patterns for image de-hazing instantly from data, leading in to more precise and feasible de-hazing outcomes. This has resulted in the deployment of many advanced networks, presenting significant improvements and success of deep learning in tackling difficulties of de-hazing an image.

A preliminary fully-formable encoder-decoder framework for de-hazing single images was presented by [24]. This architecture utilizes an encoder to remove relevant characteristics from the input images while the decoder combines and processes these depictions to generate the final de-hazed image. We apply a characteristic blend approach to handle various segments of the hazy image this technique efficiently separates and processes several inputs resulting in improved de-hazing performance.

A UCL-network architecture was introduced for the purpose of image de-hazing, utilizing multi-scale boosted and dense characteristic blend with unpaired datasets and conv.-Net. This network implements a restoration method that progressively refines the haze-free image. The decoder incorporates an iterative refinement technique network to enhance the de-hazed image incrementally by sharpening its details through several stages.

It combines channel and pixel attention elements, with the first segment featuring a novel characteristic-perception selective attention mechanism and the other utilizing a regional residual learning module. By eliminating least essential data, a method emphasizes the removal of significant data using the data, thereby enhancing the network capability to identify patterns.

Additionally, a new contrastive regularization approach using an auto-encoder framework has been introduced to reduce the memory and computational demands associated with de-hazing a single image.

Recent research has examined various deep learning procedures for de-hazing of an image, with a focus on overcoming the complications provided by the non-homogeneous haze distribution. Several studies have leveraged the D-HAZE and NH-HAZE datasets to train and evaluate their models.

The IDE (Image De-hazing and Exposure) network [25] is a specialized deep learning framework designed to improve image visibility by addressing issues of haze and exposure simultaneously. This network builds on the enhanced atmospheric scattering model to deliver more accurate de-hazing results, while also correcting underexposed or overexposed regions in an image. This net not only reduces haze but also exhibits balanced brightness and contrast.

Dehaze Net [26] is a complete convolutional neural network (CNN) that predicts the transmittance map from a foggy image, which is subsequently utilized to restore the clear image. The network is tailored to extract relevant haze-related features and estimate the degree of haze across the image efficiently. This network begins with convolutional layers that capture local features, focusing on understanding the intricate relationship between foggy inputs and their corresponding transmittance maps. These layers help extract low-level details relevant to the haze density. Intermediate layers are designed to enhance feature learning through varied receptive fields. The final layer of De-haze Net output's the estimated transmission map, which is later combined with the atmospheric light to restore the image.

FFA-Net utilizes a combination of feature extraction and attention mechanisms to enhance the de-hazing process. Its primary aim is to focus on significant features that contribute to haze removal and ignore less relevant information, thus improving the network's efficiency and output quality. This module ensures that both low-level details and high-level information are integrated effectively, helping to produce clear images.

Another promising direction is the exploration of multi-scale feature fusion techniques. By combining information from different levels of the network, these methods can effectively capture both fine-grained details and global context, leading to more accurate and visually appealing de-hazed images.

The Trident De-hazing Network [28] is named after its unique trident-like structure that effectively handles the multi-scale nature of haze distribution in images. This structure allows the network to process features at different resolutions and scales, ensuring that both fine details and broader contextual information are considered. The network is divided into three branches, each responsible for processing features at a different scale. Each branch is configured to extract features at a specific scale, enabling the network to capture small, medium, and large structures affected by haze. Then, the network incorporates a feature fusion mechanism to merge these multi-scale outputs. While this network also uses attention mechanisms, attention-based networks can be defined as neural networks that are able to determine which particular features in a hazy image are most relevant. It is possible to optimize the accuracy of the model by changing the weights of each portion of input.

Furthermore, researchers have investigated implementing of generative adversarial networks (GANs) for image de-hazing. By instructing a generator network to create realistic images without haze and a discriminator network to differentiate between actual and generated images, GAN-based approaches have shown promising image quality results and perceptual fidelity.

While these methods have achieved significant progress, there remains a need for further research to develop more robust and efficient de-hazing techniques that can handle a wide range of challenging scenarios.

Cycle Consistent Generative Adversarial Networks (Cycle-GAN) focus on transforming the haze images into non-haze images without the need for paired data to train with. Very high resolution de-hazed images can be created, however, sometimes they also contain some artifacts or alteration results based on the image hue.

To optimize the PSNR ratio of an image de-hazing system, a combination of effective loss functions, learning rates, and epochs is essential. Pixel-wise loss functions like L1 and L2 can be combined with perceptual loss functions to take both low level and high level image details. Adaptive learning rate optimizers like Adam or RMSprop can accelerate training, while learning rate scheduling techniques can prevent overfitting. Sufficient training epochs are necessary, but early stopping can help avoid overtraining. Additionally, data augmentation, regularization, and careful hyper-parameter tuning can further enhance the performance of the system.

Image De-Hazing Transformer :

Image De-Hazing Network transformer uses the window based and spatial transformation modules using an encoder-decoder framework. The encoder progressively down samples the input image to extract hierarchical features, capturing both local details and global information. The decoder then up samples these features, reconstructing a clear image while integrating high-level and low-level details. DataLoader Train and DataLoader Train Noise classes are used to prepare training datasets. These classes, load image data from specific directories and prepare them for input into a neural network.

DataLoaderEval is utilized for evaluation purposes, allowing the model to process images for testing without any augmentations or label requirements. The IDT Net framework works based on the encoder and decoder containing a window based transformer module and spatial transformer module the convolution gradually increases from input and then decreases to output.

Window-Based TM : Each encoder and decoder block within the network consists of multiple WTMs. These modules process features in localized windows, allowing the network to capture local dependencies and fine details effectively.

Spatial TM : Integrated within each block, the STM processes the feature maps to focus on broader spatial relationships and helps capture long-range dependencies. This module complements the local feature extraction performed by WTMs by expanding the perceptive range of the framework. This framework has a multi-scale, hierarchical design where the pixel density of the characteristic maps is progressively reduced and then restored. The encoder pathway captures increasingly abstract features, while the decoder pathway reconstructs the image by combining these features with skip connections from the corresponding encoder blocks.

Symmetric Skip Connections: Skip connections are used between encoder and decoder blocks, facilitating the transfer of high-resolution features to the decoding stage. This structure helps maintain detail and ensures effective feature fusion during the reconstruction process.

A deep learning architecture in PyTorch that includes IDT Block, Basic IDTLayer, Spatial Transformer Layer, and the overall IDT model. The IDT Block represents a building block incorporating attention mechanisms, specifically window-based multi-head self-attention, with optional cyclic shifts. It integrates components like MLPs (using LeFF), normalization, and Drop-Path for stochastic depth regularization.

IDTBlock Implements window-based attention with optional cyclic shifts for more context in non-overlapping partitions. Uses attention masks and FFNs (Feed-Forward Networks) with dropout paths for regularization. BasicIDTLayer builds a layer of multiple IDT Block instances, with an optional cross-attention layer (Spatial Transformer Layer). It constructs a deeper part of the model by stacking using multiple several IDT Blocks. SpatialTransformerLayer designed for spatial attention across patches in the image. It extracts and processes non-overlapping windows, performing attention within each.

IDT (Model Class): Assembles encoder-decoder structures using BasicIDTLayer, combined with projection layers (InputProj, OutputProj), and downsample/upsample modules for scaling features. The model also integrates stochastic depth for dynamic training regularization and supports checkpointing for reduced memory usage.

The IDT architecture is a neural network designed for a task that likely involves image processing or generation, such as image de-noising, super-resolution, or image-to-image translation. InputProj converts the input image to suitable format for the network typically involves a convolutional layer to extract initial features. Encoder progressively down-samples the input features and extracts higher-level features at each layer. Decoder up-samples the attributes from the encoder and refines the attributes and reconstructs the output image. Utilizing the long range skip connections, connect features from earlier encoder layers with faster convergence preserving fine-graded details. Finally, OutputProj converts the final features into the desired output and often involves a convolutional layer to produce the final image.

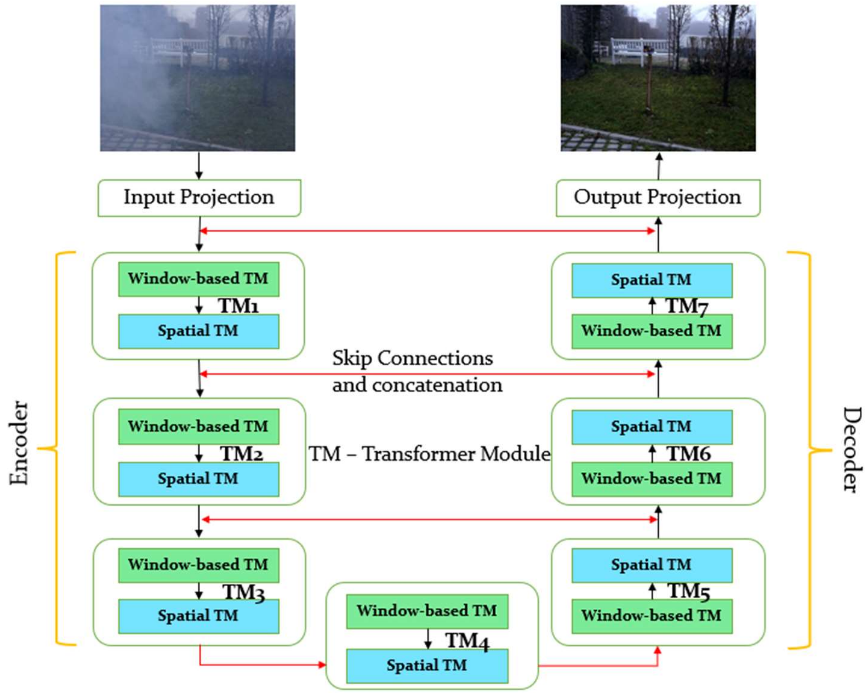
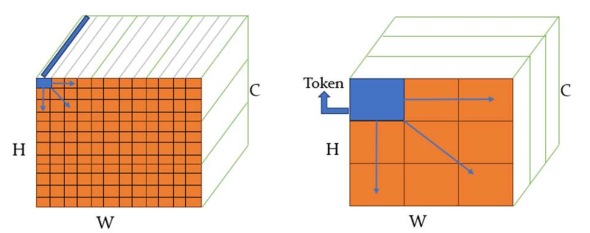


Fig.2, The structural framework of the IDT Net, which is a top-down encoder-decoder network.

Random Cropping: The net selects a random patch of a specified crop size from the input and target images to expand the diversity of training samples and enhance the model to generalize.

Flipping: Random horizontal or vertical flips are applied to both input and target images, simulating different viewing perspectives and increasing dataset diversity.



(a) For the window-based TM, In local windows the self-attention mechanism is limited.

(b) For the spatial TM, Self-attention captures long-range dependencies..

Fig.3, The figure illustrates the complementary receptive fields of window-based and spatial attention modules. Tokens are divided by gray dashed lines, and self-attention operates within window partitions marked by red solid lines.

Augmentation Selection: For noise datasets, augmentations are applied using predefined transformation functions based on a random selection. Images are loaded and converted to tensors using functions like TF.to_tensor(), ensuring compatibility with Py-Torch for further processing in neural network training. For noise data, images are also permuted from the standard (Height, Width, Channels) to the PyTorch format (Channels, Height, Width).

Normalization Layers :

The normalization layer used throughout the model (in IDTBlock, BasicIDTLayer, and SpatialTransformerLayer) is Layer Normalization (nn.LayerNorm). It normalizes the inputs across the features, making it suitable for transformer-based models where batch normalization might not perform well due to varying batch sizes. Layer normalization ensures that each iteration starts with stable, normalized features, helping the network avoid issues like vanishing or exploding gradients. The stability provided by layer normalization helps IDT-Net handle images with different haze densities more effectively. As a result, the network achieves a higher quality of de-hazing, leading to clearer, more natural images that retain essential details and color fidelity without artifacts.

Optimizer :

Adam (Adaptive Moment Estimation) is chosen for optimization due to its adaptive learning rate properties. It successfully integrates the characteristics of both Adagrad and RMSProp, adjusting the learning rate for each parameter according to the mean and variance of the gradients.

The optimizer is initialized with {optim = opt.Adam(mod.params(), lr=opt.lr, beta=(0.9, 0.999))}, where:

- mod.params() points to the network's trainable parameters.
- lr=opt.lr sets the initial learning rate.
- beta=(0.9, 0.999) regulate the decay rates for the moving averages of gradient and squared gradient estimates.

For each training batch:

- **optimizer.zero_grad():** Clears old gradients from the previous batch, ensuring that gradients do not accumulate.
- **out = model(train_x):** The model processes the input batch (train_x) to generate predictions.
- **loss = -1 * ssimloss(out, train_y):** The SSIM loss between the model's predictions and the target (train_y) is computed. It is negated to encourage maximizing the SSIM score, which indicates higher similarity between the predicted and actual images.
- **loss.backward():** Compute the partial derivatives of the loss with respect to each model parameter.
- **optimizer.step():** Optimizes the network weights using the computed gradients and the learning rate, helping to minimize the loss over time.

Learning Rate Scheduling:

scheduler = MultiStepLR(optimizer, milestones = opt.milestone, gamma=0.1) sets up a learning rate scheduler. The scheduler.step() method is called following every epoch to lower the rate of learning. at specified milestones by multiplying it by gamma=0.1. This helps in fine-tuning the model and avoids overfitting or stagnation.

Weight Updates: The optimizer modifies the network's parameters to minimize the loss (i.e., maximize the SSIM), leading to more accurate de-hazed output's over time.

Adaptive Learning: Adam fine-tunes the rate of learning for each parameter, made it suitable for complex tasks like image de-hazing where the gradient landscape might vary significantly.

Loss Functions :

In Single Image De-hazing loss functions play a vital role for training models to remove haze and improve image clarity and quality. Using IDT net we use 2 types of loss functions one is Total Variation Loss (TV Loss) and the other one is Charbonnier Loss.

- ### Total Variation Loss (TV Loss) :

Total Variation (TV) Loss is employed to simulate the resulted image to maintain spatial smoothness and noise reduction artifacts. This helps to generate more natural and realistic de-hazed images by penalizing large intensity variations between adjacent pixels.

Mathematical Representation:

$$\mathrm{TV}(x) = \lambda \cdot \frac{1}{N} \sum_{i,j} \left((x_{i,j+1} - x_{i,j})^2 + (x_{i+1,j} - x_{i,j})^2 \right)^{\beta/2}$$

Where,

- x represents the de-hazed image tensor.
- λ is the regularization coefficient, controlling the weight of the TV loss.
- β determines the degree of smoothness enforced.
- N represents the total count of elements in the image tensor and is used for normalization.

TV loss ensures that the output image maintains consistent areas with minimal abrupt intensity changes, which is essential for preserving natural details while removing haze.

The TV Loss class extends the basic TV loss into a module that can be seamlessly integrated into neural network training pipelines for image de-hazing tasks.

Equation :

$$\text{TVLoss}(x) = \text{weight} \times \frac{2}{B}\left(\frac{\sum_{i,j}(x_{i,j+1}-x_{i,j})^2}{\text{count}_w} + \frac{\sum_{i,j}(x_{i+1,j}-x_{i,j})^2}{\text{count}_h}\right)$$

where,

- B represents the batch size.
- counth is the total count of valid horizontal differences.
- countw is the total count of valid vertical differences.

- **Charbonnier Loss :**

The Charbonnier Loss is particularly effective for image restoration tasks like de-hazing due to its robustness against outliers. This loss is a smoothed approximation of the L1 loss and includes a small constant ϵ\epsilonϵ to maintain gradient stability even for very small differences.

Mathematical Representation :

$$\text{Charbonnier}(x, y) = \frac{1}{N}\sum_i \sqrt{(x_i - y_i)^2 + \epsilon^2}$$

- x and y are the input and target images, respectively.
- ϵ is small constant ensuring numerical stability.

Table1

Overview of datasets employed in our network

Datasets	Training samples	Testing samples	Evaluation Testset
Dense-Haze	50	5	D-Haze
Non-Homogeneous Haze	50	5	NH-Haze

Experimental Results and Analysis :

We provide an extensive summary of both simulated and actual datasets utilized for tasks involving single image de-hazing, specifically focusing on the D-Haze and Non Homogeneous-Haze datasets. We describe the key aspects of our implementation, the evaluation metrics employed, and the findings from our de-hazing experiments using the IDT Net. Furthermore, we validate the real-world performance of IDT Net by deploying, highlighting its robustness and effectiveness in practical applications.

Datasets :

Capturing image pairs with and without haze under identical conditions is not feasible in real-world scenarios. As a result, we utilized synthetic benchmark datasets specifically designed for haze to train and evaluate our IDT Net. Table 1 provides an outline of the simulated and actual datasets employed in the framework for simulating image de-hazing.

Implementation Details :

The IDT Net for a single image de-hazing was implemented using PyTorch and trained on a CPU. The network architecture included an module positioned between the encoder and decoder structures, with the decoder configured with [1, 1, 1, 28] blocks and the encoder containing [1, 1, 1, 28] blocks at each level. To enhance the model's generalizability, data modification methods such as horizontal flips and vertical flips were applied. The model was trained end-to-end from scratch for 100 epochs, using hyper parameters that included a decay weight of 0.0004, a size of the batch is 8, a size of the patch of 512x512, and a mutable learning rate ranging from 0.01 to 0.00001, with Adam optimizer managing the optimization process.

Evaluation Metrics :

We evaluated our network's performance across various image quality metrics, such as peak signal-to-noise ratio (PSNR), Image similarity index (SSIM). The PSNR and SSIM values were computed for the degraded images by converting them to the YCbCr color encoding and using the Y-channel for evaluation. Better PSNR and SSIM scores corresponded to high performance, indicating improved recovery of the image quality. These metrics were calculated for each pair of input and target images, and for entire dataset the average of the PSNR and SSIM scores were reported using the datasets D-Haze and NH-Haze across many networks to obtain the best quality and the results were calculated obtaining high image similarity and produce clear images.

Quantitative Evaluations :

We compared our IDT-Net with the following ten prominent de-hazing networks.: UCL [1], DEA-Net [4], U-Net [5], CycleGAN [10], Dense-Net [15], U-Net [16], IDE [25], DeHazeNet [26], FFA [27] and TDN [28]. We re-trained all networks utilizing the same ideal dataset using the identical training dataset and conducted visible contrasts to validate a good evaluation. The target estimation outcomes for simulated haze datasets are presented in Table 2. Our IDT-Net demonstrates strong performance in comparison to other networks, showing notable improvements in both PSNR & SSIM scores. On the D-Haze dataset, which focuses on outdoor hazy conditions, our network achieved marginal gains in PSNR and SSIM. More significantly, the IDT-Net exhibited substantial improvements on the NH-Haze dataset, outperforming all other networks with the good PSNR and SSIM scores, confirming its effectiveness for image de-hazing.

Qualitative Evaluations :

When comparing the de-hazed images, our model was able to recover sharper details, particularly in regions with fine textures, such as edges and distant objects, which are often challenging to restore in hazy conditions. The overall contrast in the output images was improved, with hazy regions appearing more vivid and clear, while maintaining the natural look of the scene. This was especially noticeable in outdoor hazy images, where our method managed to reduce the haze significantly without introducing artifacts such as halos or over-enhancement.

In comparison, other methods often struggled with unnatural color shifts or blur in fine details, especially in the background or distant objects. Our network, on the other hand, retained the consistency of natural colors and minimized visual distortions.

Table2 : Comparison between the PSNR and SSIM using datasets D-Haze and NH-Haze using different metrics.

Datasets	**D-Haze**	**NH-Haze**
Metrics	**PSNR/SSIM**	**PSNR/SSIM**
IDE [25]	16.503/0.742	16.40/0.61
DeHazeNet [26]	16.905/0.811	14.90/0.702
FFA [27]	20.23/0.710	19.50/0.644
TDN [28]	20.73/0.673	20.06/0.713
Proposed Net	24.90/0.91	21.51/0.91

Training on D-Haze:

- The model should achieve high PSNR and SSIM scores using IDT 24.90 dB and 0.91 respectively compared to other metrics IDE [25], De-HazeNet [26], FFA [27], TDN [28]due to the synthetic nature of the dataset, which provides consistent training data.
- **Challenges**: The synthetic hazes in D-Haze may lead to overfitting, resulting in a model that performs well on synthetic benchmarks but struggles with real-world generalization.

Training on NH-Haze:

- The real-world nature of NH-Haze introduces variability, making training more challenging but leading to better generalization to real-life scenarios.
- **Analysis**: The PSNR and SSIM scores on NH-Haze are generally lower than D-Haze due to the complexities of real haze 21.51 dB and 0.91 respectively. However, models trained on NH-Haze show better real-world performance and robustness.

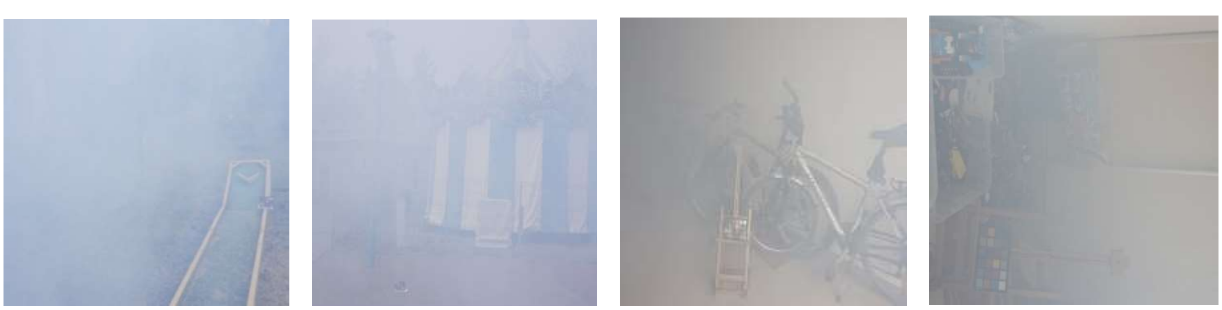


Fig.4, Single Image De-hazing results using D-Haze dataset on IDT Net.

Fig.5, Single Image De-hazing results using NH-Haze dataset on IDT Net.

Performance Comparison:

- **Model Performance:** When trained and tested on D-Haze, IDT Net should show strong quantitative metrics, but may exhibit performance drops when tested on non-simulated hazy images due to the distribution gap.

Training on NH-Haze offers insights into the model's ability to generalize across varied real-world conditions, which is more indicative of actual use-case performance.

Combining D-Haze for initial pre-training (for stability and high-quality synthetic de-hazing) and fine-tuning on NH-Haze can enhance both metrics and visual performance.

Ablation Studies:

Analysing the impact of key components like data augmentation, SSIM loss contribution, and learning rate scheduling helps refine the training strategy for improved results.

This study introduces an innovative approach for single image de-hazing using the IDT network, which is designed to enhance image clarity by efficiently removing haze. The network architecture is tailored to capture multi-scale features while preserving fine image details. We trained the model using the D-Haze and NH-Haze datasets, encompassing a range of indoor and outdoor scenes with various levels of haze.

Performance was evaluated through quantitative metrics such as PSNR and SSIM, alongside qualitative visual assessments. Results indicate that our method performs competitively or better in contrast to the current cutting-edge methods. Notably, the network demonstrated significant improvements in generating clearer images with enhanced contrast and detail. The increased PSNR and SSIM scores confirm the model's capability in handling complex de-hazing tasks effectively.

Conclusion :

In this research, we present a groundbreaking Image De-hazing Transformer Network (IDT-Net), which does not require paired training data. Instead, it utilizes a set of carefully designed loss functions, refined activation and layer normalization with an Adam Optimizer to evaluate the quality of the de-hazed output, guiding the network's learning process. While there are areas for further improvement, IDT-Net demonstrates superior performance in enhancing image brightness and preserving fine details in contrast to the current cutting-edge approaches. The network is also lightweight and highly efficient, making it ideal for real-time applications, including video de-hazing. Future work could focus on extending IDT-Net to video de-hazing and also works on O-Haze, I-Haze by incorporating temporal consistency terms into the loss functions for better coherence across frames.

Drawbacks :

While Image De-hazing Transformers (IDTs) have shown promising results in single image de-hazing, their performance is still limited by several factors, especially when trained on datasets like DHAZE and NH-HAZE. Due to these datasets are limited not high, may not capture the full range of real-world haze conditions. This can lead to models that are overfitted to specific types of haze. IDTs can be sensitive to noise in the input images and can sometimes introduce color distortions and halo artifacts, especially in regions with high contrast or complex textures. This can degrade the visual quality of the de-hazed images.

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