World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:16, No:11, 2022

NDENet: End-to-End Nighttime Dehazing and Enhancement

H. Baskar, A. S. Chakravarthy, P. Garg, D. Goel, A. S. Raj, K. Kumar, Lakshya, R. Parvatham, V. Sushant, B. Kumar Rout

***Abstract*—**In this paper, we present a computer vision task called nighttime dehaze-enhancement. This task aims to jointly perform dehazing and lightness enhancement. Our task fundamentally differs from nighttime dehazing – our goal is to *jointly* dehaze and enhance scenes, while nighttime dehazing aims to dehaze scenes *under a nighttime setting*. In order to facilitate further research on this task, we release a benchmark dataset called Reside-β Night dataset, consisting of 4122 nighttime hazed images from 2061 scenes and 2061 ground truth images. Moreover, we also propose a network called NDENet (Nighttime Dehaze-Enhancement Network), which jointly performs dehazing and low-light enhancement in an end-to-end manner. We evaluate our method on the proposed benchmark and achieve Structural Index Similarity (SSIM) of 0.8962 and Peak Signal to Noise Ratio (PSNR) of 26.25. We also compare our network with other baseline networks on our benchmark to demonstrate the effectiveness of our approach. We believe that nighttime dehaze-enhancement is an essential task particularly for autonomous navigation applications, and hope that our work will open up new frontiers in research. The code for our network is made publicly available.

***Keywords*—**Dehazing, image enhancement, nighttime, computer vision.

I. Introduction

THE presence of dust, smoke, mist, and other particles in the atmosphere often leads to blurring, colour distortion, and low contrast in images. Images affected by haze are more challenging for downstream tasks. Image dehazing is crucial in applications where real-time image capture is necessary, such as autonomous navigation, remote sensing, surveillance, etc.

Daytime dehazing is a well-explored task in computer vision. Traditional approaches for daytime dehazing require image priors in order to perform dehazing. However, these priors do not apply to images captured in the nighttime. For example, the dark channel prior [1] does not hold when the colours of objects in scene are very similar to the atmospheric lighting, as is the case in a nighttime scene. Therefore, learning-based dehazing approaches were introduced to overcome these issues. However, dehazing is much more challenging when there is insufficient lighting during image capture. Such a low-light setting leads to low contrast, loss of essential details and thus degrades visibility and image quality. In such settings, even learning-based daytime dehazing algorithms fail [3]. When nighttime images are used for downstream computer vision approaches have been proposed to solve this task. However, nighttime dehazing approaches still leave object details unclear and lead to colour distortion, which make them unusable for downstream computer vision tasks (Fig. 1). This calls for greater exploration to enhance the image illumination for better performance on downstream tasks.

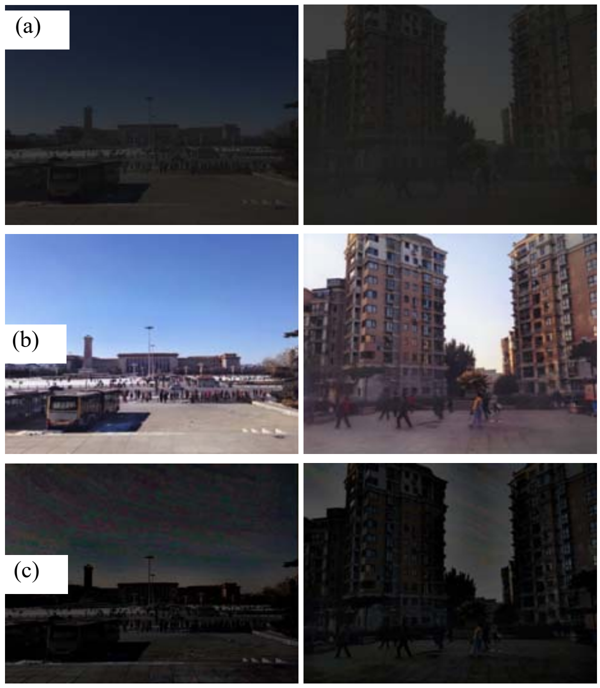

Fig. 1 The problem with nighttime dehazing methods. While the haze has been removed to an extent, the details are still hidden due to low illumination. (a) Nighttime hazy images, (b) Our method, (c) Maximum Reflectance Prior (MRP) [2]

In this task, a nighttime hazed image is jointly dehazed and illumination enhanced. This task can be understood as a combination of low-light image enhancement and nighttime image dehazing. Additionally, to motivate further research on this task, we introduce a large scale dataset called *Reside-β Night* dataset. Our dataset consists of 4122 nighttime hazed images generated from 2061 scenes, and 2061 corresponding ground truth images from the Reside-β dataset. Each scene contributes two images to our dataset, varying in the

Harshan Baskar*, Anirudh S Chakravarthy, Prateek Garg, Divyam Goel, Abhijith S. Raj, Kshitij Kumar, Lakshya, Ravichandra Parvatham, and V. Sushant are with Center for Robotics and Intelligent Systems, BITS Pilani, India (*e-mail: f20180166@pilani.bits-pilani.ac.in).

Bijay Kumar Rout is with Center for Robotics and Intelligent Systems, BITS Pilani, India and with Department of Mechanical Engineering, BITS Pilani, India.

atmospheric scattering coefficient β [4], which controls the amount of haze. Our dataset can not only serve as a benchmark for this task, but also for other related tasks such as single image dehazing, video dehazing, and low-light image enhancement. Moreover, we also propose a deep learning-based algorithm called NDENet to solve nighttime image dehazing. Our network is based on Retinex theory, where we aim to improve the image quality by processing the illumination and reflectance. NDENet jointly performs the task of haze removal and light enhancement in an interrelated and end-to-end manner. We argue that by jointly solving the two tasks in an end-to-end fashion, we can leverage the complementary nature of the two tasks to produce high quality and clear images. We also propose and evaluate several baseline algorithms using state-of-the-art algorithms for single image dehazing and low-light image enhancement. Experimental results clearly demonstrate the effectiveness of performing dehazing and enhancement together. The dataset and code will be made public upon acceptance.

The key contributions of our paper are as follows:

- We present a computer vision task called Nighttime Dehaze-Enhancement.
- We create the first large-scale dataset for this task, consisting of 4122 images along with 2061 clear ground truths.
- We present an approach called NDENet for simultaneously dehazing and illuminating a scene.

II. Related Work

Single Image Dehazing

Most traditional single image dehazing methods build upon the Atmospheric Scattering model [4]. Under this optical model, the hazy image (I) is decomposed into transmission maps (t), global atmospheric illumination (A), and clear image (J) using (1). Several dehazing methods [5]-[8] use the scattering model.

$$J(z) = \frac{I(z)-A\left(1-t(z)\right)}{t(z)} \tag{1}$$

Approaches following the atmospheric scattering model can be classified under two categories: *prior-based* and *learning-based*. The prior-based approach estimates the transmission maps and global atmospheric illumination using image priors. Dark Channel Prior [1] estimated the transmission map based on empirical evidence that in an RGB image, one of the three colour channels is of significantly lesser intensity than the other two. Zhu et al. [9] proposed the Colour Attenuation Prior (CAP), which performs dehazing based on the correlation of haze with the difference between brightness and saturation at each patch. Non-Local Colour Prior [10], Change of Detail [11] and Colour Ellipsoid [12] are few other prior-based methods.

Prior-based methods fail to generalize to challenging environments, such as nighttime images, and learning-based methods attempt to learn the transmission map from the training data. Some methods estimate the transmission map (following the atmospheric scattering model) while others learn an end-to-end (RGB-to-RGB) dehazed image. Cai et al. introduced DehazeNet [13], one of the first RGB-to-RGB learning-based methods for single image dehazing. Zhang et al. proposed DCPDN [14], which used a GAN to estimate the transmission map and the atmospheric light. Cycle-Dehaze [15] used a cycle-GAN to perform dehazing. Qin et al. proposed FFANet [16] which performs RGB-to-RGB dehazing using Feature Attention (FA). BPPNet [17] introduced Pyramid Convolution (PyCon) for dehazing using multiple input scales. The proposed nighttime dehaze-enhancement not only requires successful dehazing, but also enhancement of the image to make it usable for downstream tasks.

Nighttime Dehazing

Nighttime dehazing has recently gained prominence in literature, as daytime dehazing approaches often fail to generalize over nighttime scenes. Pei and Lee [18] proposed a colour transfer-based model augmented with dark channel prior and bilateral filter for haze removal. Li et al. [19] solved non-uniform lighting by incorporating a glow factor alongside the atmospheric map and transmission estimation. Ancuti et al. [20] computed patch-wise airlight components to deal with non-uniform lighting. Park et al. [21] alleviated the haze and glow effect by estimating atmospheric light and transmission map using a weighted entropy. Zhang et al. [22] targeted varying ambient illumination conditions by introducing a reflectance prior (MRP). OS-MRP [23] addressed the problem of colour correction and haze removal sequentially.

To reduce colour distortion and halo effects during nighttime dehazing, Yu et al. [24] proposed the estimation of transmission map using a pixel-wise alpha blending method. Lou et al. [25] approached halo-free nighttime dehazing by using a linear learning model and a colour-dependent MRP. SIDE [26] solved both night light enhancement and haze removal in a sequential manner by considering illumination and halo effects. Tang et al. [3] propose the use of Taylor series expansion for estimating the point-wise transmission map along with Retinex theory. Feng et al. [27] used an autoencoder to estimate the transmission map and a guided filtering method to obtain ambient illumination. Nighttime dehazing approaches only focus on removing haze from nighttime images but do not enhance the image illumination, making it different from our task.

Low-Light Image Enhancement

The earliest illumination or contrast enhancement techniques utilised various conventional computer vision operations like increasing the brightness, saturation or dynamic range of the image, and Gamma Correction (GC). Later, histogram-based approaches [28]-[31] were introduced, which were far more successful. The Retinex theory [32] has also been leveraged for enhancement [33], [34], through which the image is decomposed into its illumination and reflectance components, following which the illumination map is enhanced. Recently, deep learning has also been used for this task [35]-[38]. Low-light image enhancement does not involve removing haze or noise from the scenes and only focuses on increasing illumination.

III. Reside-β Night

Since none of the existing benchmarks are suitable for the task of nighttime dehaze-enhancement, we create a large-scale benchmark for evaluation of algorithms on this task. This benchmark must satisfy several criteria. First, it must consist of nighttime hazed and corresponding dehazed image pairs. Second, since the nighttime hazed image is synthetic, it must be created by some non-trivial method consisting of challenging patterns of haze and varying degrees of illumination. Finally, the synthetic image must also appear realistic, so that the algorithms trained on this dataset can be used in real-world applications.

Keeping the criteria mentioned above in mind, we present a dataset called the *Reside-β Night*. We construct our dataset using hazed and dehazed image pairs from the Reside-β dataset [39].

The dataset is generated from the Reside-β Outdoor Training Set (OTS) dataset [39] which consists of 2061 scenes. Each scene contains 35 hazed images and one corresponding clear image, having a total of 72,135 hazed images and 2061 clear images. Each of the 35 hazed images from every scene is synthetically generated by varying A (global atmospheric light) and β (scattering coefficient of atmosphere) parameters associated with the atmospheric scattering model. We select a subset of images from Reside-β OTS dataset which has a parameter of $A = 1$ and $\beta \in \{0.08, 0.16\}$. The resulting 4122 hazed images are split in 3:1 ratio into training and test sets, containing 1541 and 520 images respectively. Next, the hazed images are transformed into Hue, Saturation, Value (HSV) colour space, where the images are darkened. Finally, a GC is performed to reduce illumination. This serves as our nighttime dehaze-enhancement dataset.

Reside-β Night is a large-scale dataset for nighttime dehaze-enhancement. This benchmark could also prove useful for similar tasks such as single image dehazing, video image dehazing, and low-light image enhancement. We believe our dataset will serve as a useful benchmark for various dehazing tasks, thereby enabling stronger performance on downstream scene understanding tasks.

IV. NDENet

Our network for nighttime dehaze-enhancement is illustrated in Fig. 2. The proposed network consists of three stages: 1) Decomposition, 2) Illumination Enhancement, and 3) Dehazing. The decomposition module is inspired from Retinex theory, where the input image is decomposed into corresponding reflectance and illumination components. The illumination enhancement module brightens the illumination map in a structurally aware manner. Finally, the dehazing module eliminates noise and haze. We explain our network in detail in the following sections.

A. Decomposition

Retinex theory aims to explain the colour perception during human vision. Under this theory, an image is assumed to consist of illumination and reflectance components. Concretely, the decomposition of an image S is given as:

$$S = I \circ R \tag{2}$$

where I and R denote the illumination and reflectance respectively, and $\circ$ represents the element-wise product. Illumination indicates the lightness in the image. Reflectance denotes the intrinsic characteristic of objects in the image which lead to the sensation of colour. The illumination and reflectance components are independent to each other. However, Retinex decomposition is an ill-posed problem [36] and requires handcrafted tuning, which fails to generalize to challenging low-light conditions. Therefore, we approximate the Retinex decomposition using a convolutional neural network (CNN).

We model the decomposition CNN using a U-Net architecture [40]. Given an input RGB image, the decomposition network outputs the corresponding illumination and reflectance components for the image. During training, the network decomposes the nighttime haze and corresponding dehazed images to their illumination and reflectance components. However, since ground-truths are not available for illumination and reflectance, the decomposition is guided using loss functions to impose several constraints. Three loss functions are used to train the decomposition network: reconstruction loss (L_{recon}), reflectance similarity loss (L_{rs}), and illumination smoothness loss (L_{is}).

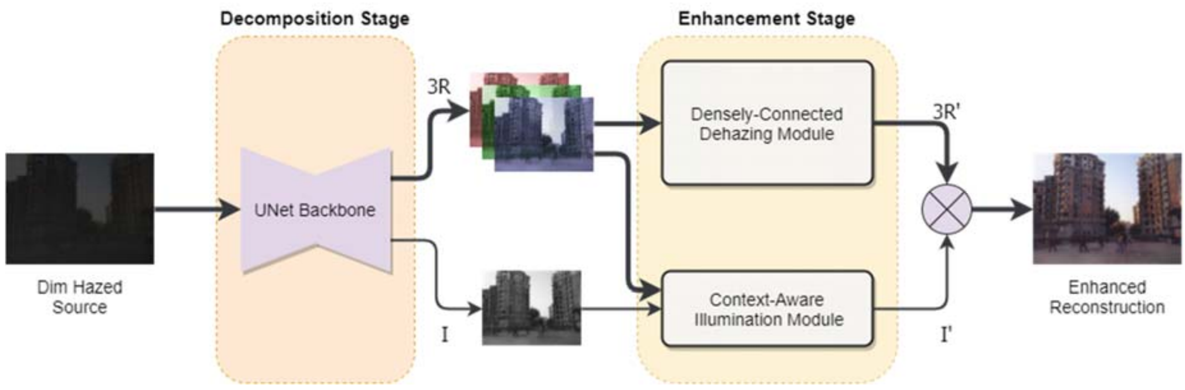

Fig. 2 The proposed NDENet architecture

The decomposition network decomposes the nighttime hazed image S_N and dehazed image S_D to illumination (I_N,I_D) and reflectance components (R_N,R_D). To ensure that the learnt decomposition follows the Retinex theory, we use the following reconstruction loss:

$$L_{decom} = \sum_{i\in\{D,N\}} \sum_{j\in\{D,N\}} \lambda_{ij} || R_i \circ I_j - S_j || \qquad (3)$$

where λ_{ij} denotes the weight assigned to the reconstruction combination. Since reflectance is an intrinsic property of objects in the image, R_D and R_N must be similar while the illumination varies. To ensure that the learnt reflectances maintain this property, a given image S_i is reconstructed using its illumination map I_i and *both* reflectance maps R_D and R_N. In other words, the reflectance for the hazed image is used to reconstruct the hazed image as well as the dehazed image, thereby ensuring that the reflectances R_D and R_N are similar. In addition, a direct reflectance similarity constraint ensures that the reflectances R_D and R_N are similar by minimising the following loss function:

$$L_{rs} = \|R_N - R_D\| \qquad (4)$$

The learnt illumination must be locally consistent and preserve the structure to maintain smooth texture details [41]. Therefore, we use the illumination smoothness loss as in [36]. The Total Variation minimisation (TV) [42] is structure agnostic, and therefore, is weighted using the gradient of reflectance to introduce texture and boundary context. This illumination smoothness loss is given as:

$$L_{is} = \sum_{i\in\{D,N\}} ||\nabla I_i \cdot \exp(-\lambda_s \nabla R_i) || \qquad (5)$$

where λ_s denotes the weight assigned to the structure awareness from the reflectance gradient. At the boundaries, the gradient is steep which introduces discontinuity in the learnt illumination.

B. Illumination Enhancement

Several handcrafted approaches have been explored to adjust the lightness of low-light images. However, these approaches fail to generalize well for images captured across challenging conditions such as dim lighting and low colour contrast. Therefore, we use a CNN to perform brightness adjustment and enhance illumination.

The input to the network is the Retinex decomposition for the nighttime hazed image. In other words, reflectance components of the nighttime hazed image are input into the network. The output of the enhancement network is the brightened illumination map. The reflectance is also used as an input so that the network can learn to adjust the illumination of the image in a context-aware manner. Concretely, this enables the network to dynamically enhance the brightness of specific objects not only using shape information from the illumination map, but also using the colour and texture information from the reflectance map. We use 11 convolution layers in the enhancement network with residual connections at each stage.

C. Dehazing

Greater noise is often encountered in nighttime images. While illumination enhancement adjusts the image brightness, it also results in haze amplification. Hence, the reflectance component needs to be dehazed to eliminate noise. Traditional daytime dehazing approaches use optical models with priors such as the dark channel prior, CAP, etc. However, several of these priors do not hold for nighttime haze images due to the presence of several artificial sources of light [3]. Therefore, these methods struggle to dehaze nighttime images and often lead to unnatural outputs consisting of drastic colour distortion and halo artifacts. Therefore, we apply a learning-based algorithm to perform reflectance dehazing.

We follow a state-of-the-art single image dehazing network, namely, Densely Connected Pyramid Dehazing Network (DCPDN) [14], for this purpose. Specifically, we use the transmission map estimation network with the objective of reflectance dehazing. Our network consists of an encoder-decoder structure with densely connected blocks to improve feature information flow for robust feature learning. Additionally, a multi-level pyramid pooling is used to capture context from multiple scales. The decoder consists of bottleneck blocks with residual connections, with transition blocks introduced to restore the resolution lost due to upsampling operations.

The first three dense blocks of DenseNet-121 [43] are used as the encoder network, with four pooling sizes of 1/32, 1/16, 1/8, 1/4 used in the pyramid pooling layer. Each Bottleneck layer consists of two *BatchNorm-Conv-ReLU-Dropout* mini-blocks.

D. Reconstruction

The adjusted illumination and dehazed reflectance components are used to reconstruct the dehazed image using (2). The image reconstruction loss is formulated by minimizing the mean-squared error between the reconstructed image S_Y and target dehazed image S_D. In addition, we also use self-supervision to ensure robust decomposition by minimizing the mean-squared error between the respective illuminations (I_D and I_Y) and reflectances (R_D and R_Y). This reconstruction loss L_{MSE} is given as:

$$L_{MSE} = \sum_{F\in\{I,R,S\}} \lambda_F ||F_Y - F_D||^2 \qquad (6)$$

where λ_F denotes the weight assigned to each loss function. Moreover, to ensure the perceptual similarity between S_Y and S_D, we use the VGG-based edge-preserving loss [44], [45]. The edge-preserving loss minimises the feature-level difference between the two images using a pre-trained VGG network ϕ. This difference is computed at each layer i of the VGG feature extractor. The edge-preserving loss is formulated as:

$$L_{VGG} = \lambda_\emptyset \sum_i w_i ||\emptyset(S_Y)_i - \emptyset(S_D)_i||^2 \qquad (7)$$

where λ_ϕ denotes the weight assigned to the edge preserving loss, and w_i denotes the weight of each layer towards the edge-preserving loss. The final reconstruction loss is:

$$L_{recon} = L_{VGG} + L_{MSE} \qquad (8)$$

V. Experiments

In this section, we demonstrate the effectiveness of the proposed algorithm by conducting several qualitative and quantitative comparisons with state-of-the-art methods for single image dehazing and low-light enhancement on the Resideβ Night dataset.

A. Implementation Details

Following the training protocol in [36], the network is trained in two stages. In the first stage, we train the Retinex decomposition network individually. The input images and corresponding ground truths in the decomposition UNet are cropped to a size of 256 × 256. We use 32 channels in the first layer of the UNet to maintain a small memory footprint for the decomposition network. In the second stage, the weights of the decomposition network are not updated, and the remaining network is trained.

While training the decomposition module, the network is fed nighttime hazed images as well as the corresponding dehazed images with shared weights, and it outputs reflectance and illumination for both. However, for the second stage, the entire network is used but the decomposition part of the network is frozen. Only the nighttime hazed image is fed to the decomposition module, and the corresponding reflectance and illumination are subsequently enhanced by the enhancement module in the second stage.

In both training stages, we use an Adam optimizer with a learning rate of $2.5e-4$ to train the networks. The first and second stages are trained for 55 and 25 epochs, respectively, with a batch size of 2. An Nvidia T4 GPU is used for to train our network. We also apply data augmentation methods (random resizing, cropping) during training.

For L_{decom} (3), we use $\lambda_{DD} = \lambda_{NN} = 1$, $\lambda_{ND} = 0.01$ and $\lambda_{DN} = 0.001$. For the reconstruction MSE loss L_{MSE} (6), we set $\lambda_S = 1$, $\lambda_I = 0.01$, and $\lambda_R = 0.05$. For the edge-preserving loss (7), we use $\lambda_\phi = 1$ with weights of $[8,4,2,1]$ for each VGG layer.

B. Results

We evaluate our method against four state-of-the-art approaches on single image dehazing and low-light image enhancement. For single image dehazing, we evaluate DCPDN [14] and FFANet [16], and for low-light image enhancement, we evaluate Zero-DCE [38] and KinD++ [37]. However, we note that direct inference through these networks is not a fair comparison, as they are trained with different objectives. Therefore, we cascade the single image dehazing and low-light enhancement in different orders to compare our approach. In Table I, the image is first enhanced using the enhancement network and then dehazed, while in Table II, the order is reversed, i.e., the image is first dehazed and then enhanced. In Table III, our method is compared against two nighttime dehazing methods: DNU [46] and MRP [2].

We also demonstrate the qualitative performance of NDENet in Fig. 3 and compare it with the four best-performing combinations of dehazing and enhancement networks. We note that performing low-light enhancement first followed by dehazing results in a mute tone but hazy image. Performing dehazing first produces more colour contrast, yet the image texture and sharpness do not remain consistent throughout the image. We observe that FFANet – Zero-DCE performs well in dehazing but does not increase the illumination, while FFANet – KinD++ is able to recover the original brightness of the image while leading to unnatural sharpness and colour contrast. In all compared methods, regions of the image having higher haze density still appear hazy. However, our approach is able to dehaze the scene successfully, while maintaining texture consistency throughout.

TABLE I
Quantitative Comparison of the Proposed Method with Baselines

Low-Light	Dehazing	SSIM	PSNR
Zero-DCE	DCPDN	0.7321	13.26
Zero-DCE	FFANet	0.7993	15.16
KinD++	DCPDN	0.5007	9.63
KinD++	FFANet	0.5874	14.15
NDENet (proposed)		0.8962	26.25

The image is first passed through a low-light enhancement network followed by a dehazing network.

TABLE II
Quantitative Comparison of the Proposed Method with Baselines

Dehazing	Low-Light	SSIM	PSNR
DCPDN	Zero-DCE	0.6345	9.61
DCPDN	KinD++	0.6774	11.72
FFANet	Zero-DCE	0.8159	15.10
FFANet	KinD++	0.5639	15.16
NDENet (proposed)		0.8962	26.25

The image is first passed through a dehazing network followed by a low-light enhancement network.

We also evaluate our network against two open-source nighttime dehazing methods – DNU [46] and MRP [2] in Table IV. We use two settings: direct nighttime dehazing and cascaded with low-light enhancement networks. We also compare the qualitative performance of our network with two direct nighttime dehazing methods and the two best performing cascade methods in Fig. 4.

Clearly, the dehazed outputs from other approaches still contain noise, making them unusable for downstream tasks. The nighttime dehazing methods increase the contrast, evident in plain textures like sky and roads, while ruining the texture. The MRP – Zero-DCE cascade results in a mute tone with observable noise and high saturation at the objects edges. The DNU – Zero-DCE cascade results in high degree of noise with noticeable colour distortion. However, our method is able to maintain the colour and texture details well. Our method consistently outperforms all baselines, achieving an SSIM of 0.8962 and a PSNR of 26.25.

TABLE III
Quantitative Comparison of the Proposed Method with Nighttime Dehazing Algorithms

Nighttime Dehazing	SSIM	PSNR
MRP [2]	0.3165	7.66
DNU [46]	0.3825	8.15
NDENet (proposed)	0.8962	26.25

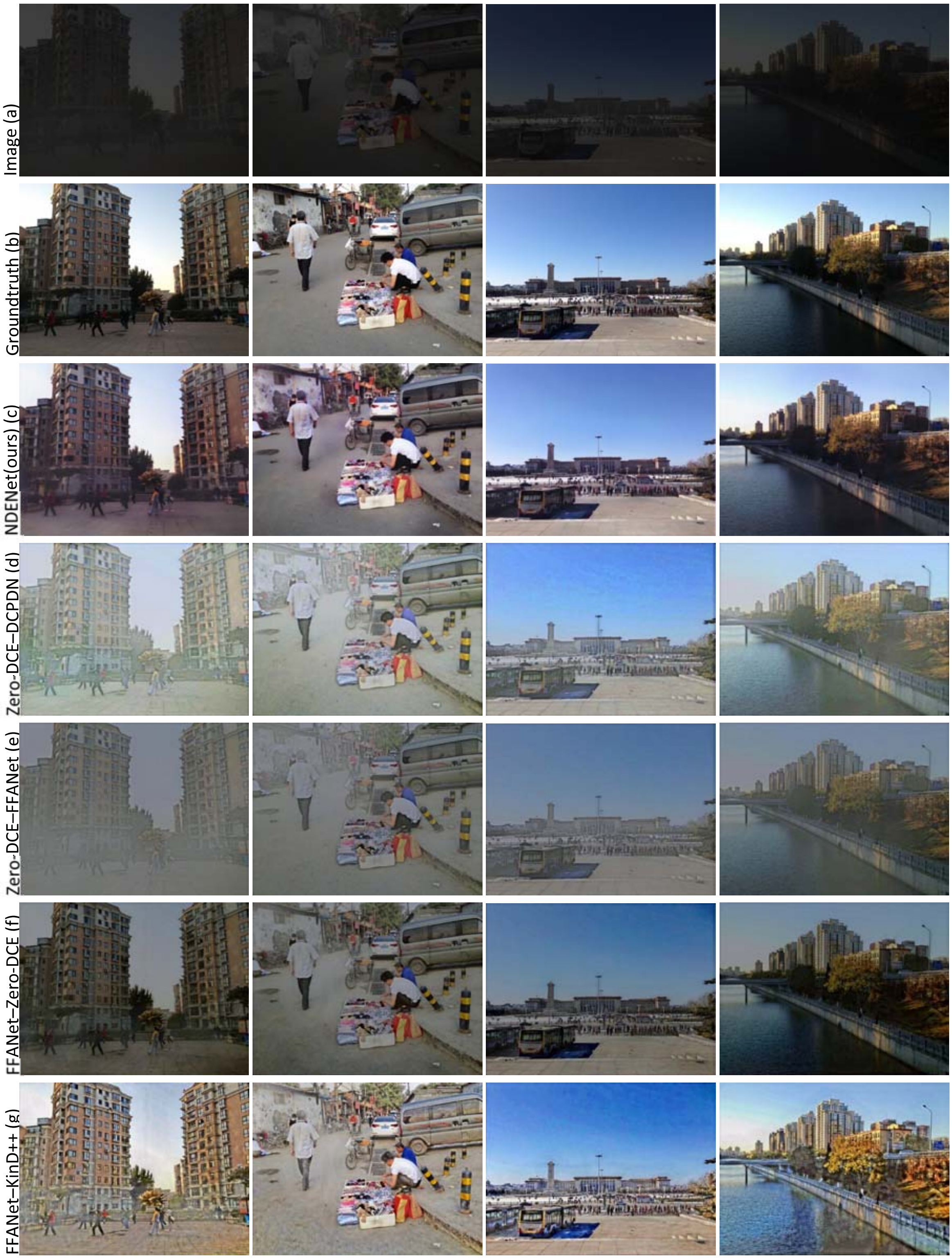

Fig. 3 Comparison of results obtained using our approach (c) with other state-of-the-art methods cascaded together. Only the top-4 previous methods are showcased here. Clearly, our method is able to brighten images while maintaining details across hazy conditions

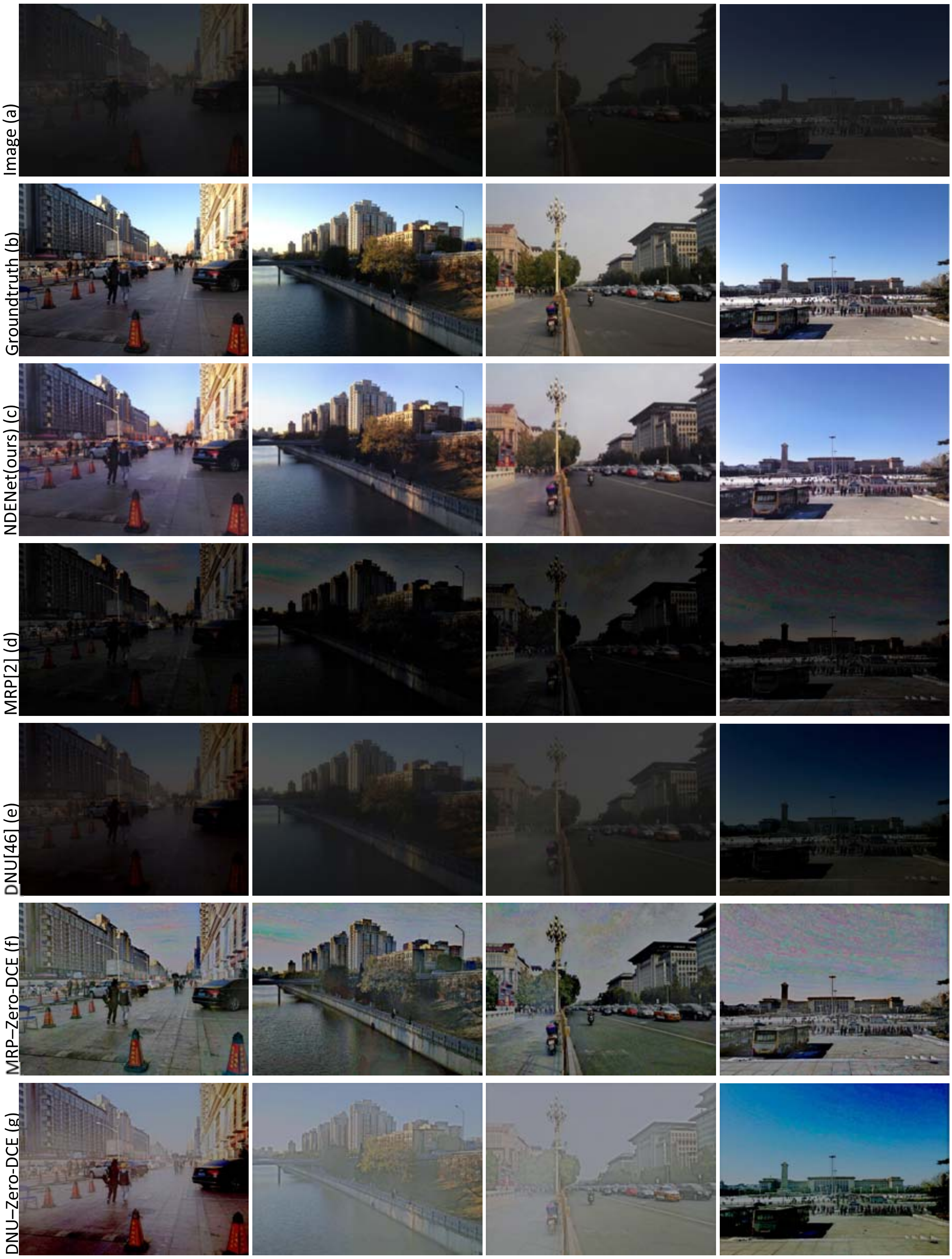

Fig. 4 Comparison of results obtained using our approach (c) with other publicly available nighttime dehazing methods. Clearly, the previous night time methods struggle to generate images with visible details. Cascading enhancement networks (last two rows) distorts the image quality as well

VI. Conclusion

We present a computer vision task named as nighttime dehaze-enhancement along with a new large-scale dataset called the Reside-β Night dataset. This task combines nighttime image dehazing and low-light image enhancement, with an objective to jointly dehaze and enhance illumination. We also propose an algorithm, NDENet, as a baseline algorithm with SSIM of 0.8962 and PSNR of 26.25, for future research on this task. We believe this task will motivate the research community to develop ideas for scene understanding tasks, especially involving challenging nighttime scenes.

TABLE IV
QUANTITATIVE COMPARISON OF THE PROPOSED METHOD WITH NIGHTTIME DEHAZING ALGORITHMS CASCADED WITH A LOW-LIGHT ENHANCEMENT NETWORK

Nighttime Dehazing	Low-Light	SSIM	PSNR
MRP	Zero-DCE	0.6871	14.56
MRP	KinD++	0.5116	13.39
DNU	Zero-DCE	0.7313	14.79
DNU	KinD++	0.5794	13.83
NDENet (proposed)		0.8962	26.25

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