Non-Homogeneous Haze Image Formation Model based Single Image Dehazing

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Abstract— **Image dehazing is an image processing technique that involves removing the haze effect from a given image. Restoration of hazy images is currently an established computer vision issue due to its applications in the real world, like automated vehicles, surveillance, etc. This paper proposes a single image dehazing model by estimating atmospheric light and transmission map simultaneously using two networks. Atmospheric light and transmission map are estimated by a non-homogeneous light estimation network and a novel refined transmission map estimation network. The non-homogeneous light estimation network has two subnetworks: a white-balanced network and a deep convolutional neural network called Global Atmospheric Light Estimation Network. The white-balanced error network for correction of white-balanced error in a hazy image and a Global Atmospheric Light Estimation Network for estimation of global atmospheric light in a corrected white-balanced error hazy image. A refined transmission map estimation network is used to create a refined transmission map of the hazy image. The design of a refined transmission map estimation network is based on U-Net with skip connections, which estimates and refines the transmission map of the input haze image. The non-homogeneous haze image formation model takes both estimated global atmospheric light and a refined transmission map as input to restore the hazy-free image. The global atmospheric light estimation network and refined transmission map estimation network are trained using mean square error (MSE) and hybrid loss functions, respectively. In terms of structural similarity index Matric (SSIM) and peak signal-to-noise ratio (PSNR), the proposed model is equal to the cutting-edge approaches on the NR-Haze, I-Haze, and O-Haze datasets.**

Keywords—PCA, KNN, White-Balanced network, Deep Convolutional Neural Networks (DCNN), Auto-encoder, Residual network, Attention map.

I. INTRODUCTION

Restoration of Hazy Image (HI) is a dehazing problem in which the user tries to remove the haze effects that appear in the captured images. Single image Dehazing (SID) comes under the broad research area of computer vision and is one of the well-known problems that restores the clear image of a scene from the hazy images captured under various inclement weather conditions. Haze occurs in the atmosphere when dust, fog, smoke, and other particles are present in such quantities as to obscure the visibility of the scene. This is an inversely ill-posed problem. Many methods are proposed for image dehazing using traditional and artificial intelligence. Narasimhan et al. [3] introduced the atmospheric scattering model (ASM) based on the physical model of the atmosphere. Some authors refer to ASM as the Hazy Image Formation Model (HFM) [21], which is defined as eq. (1).

$$H(u) = C(u)T(u) + A(1-(T(u)) \quad (1)$$

$$T(u) = e^{-\gamma d(u)} \quad (2)$$

where, $H(u)$ is the (HI), $C(u)$ is the haze-free image (HFI), T is the transmission map, γ is haze coefficient, $d(u)$ is the distance from object to camera and A is the global atmospheric light factor. To estimate the C, dehazing methods aim to determine the unknown components T and A. The estimated T & A are further used in the following equation to reconstruct of C.

$$C(u) = \frac{H(u)-A}{T(u)} + A \quad (3)$$

In the preceding eq. (3), A may usually be considered to be constant throughout the image, however in most of the cases, A is intermittent from pixel to pixel, making the image heterogeneous. To deal with the heterogeneity, a modified ASM know as Non-Homogeneous Hazy Image Formation Model (NHHFM) is defined as:

$$H(q,r) = C(q,r)T(q,r) + A(q,r)(1-\left(T(q,r)\right) \quad (4)$$

where q, r are the indices used in H, C, T, and A from NHHFM, the haze free image modified C can be reconstructed as:

$$C(q,r) = \frac{H(q,r)-A(q,r)}{T(q,r)} + A(q,r) \quad (5)$$

After estimating the global atmospheric light from a Non-Homogeneous Atmospheric Light image. The reconstruction equation can be re-written as:

$$C(q,r) = \frac{H(q,r)-A}{T(q,r)} + A \quad (6)$$

Our proposed method uses the NHHFM model. The hazy image is passed through the non-homogeneous light estimation network (NHLEN) and the refined transmission map estimation network (RTEN). NHLEN has two subnetworks: a white-balanced error network (WBEN) and a Global Atmospheric Light Estimation Network (GALEN) for estimating the atmospheric light of the hazy image. WBN extracts principal component analysis (PCA) features from the input image and the K-nearest neighbour (KNN) on the intrinsic (Set 1) dataset for white-balanced error correction. The intrinsic (Set 1) dataset has the images that were taken in different light conditions. GALEN takes a corrected white-balanced error image as input and gives global atmospheric light as output. RTEN is specially designed for estimating refine transmission map based on U-Net an end to end trainable network to estimating refined transformation map by taking hazy image as input and produce refined transmission map as output. Global atmospheric light and a refined transmission map are used by NHHFM to reconstruct a HFI by using eq. (6). Using different datasets, the proposed method is compared with other well-known methods in the literature in terms of SSIM and PSNR. RTEN is our contribution which is used as plug in network for any network which uses ASM model.

The remainder of this paper is organised in the following way: In Section II, relevant work is discussed. Section III explains the proposed method, whereas Section IV shows the outcomes of the experiments. Section V concludes the proposed work.

II. RELATED WORK

In the early 1990s, Bisssonnrette [1] presented the solution to blurred images due to forward-scattered radiation. Later, following this idea, Oakley and Satherley [2] used real degraded images to study the dehazing under severe weather conditions and obtained better results. After that, Narashimhan and Nayar [3] introduced the ASM, which opened a new direction for research. In the 20th century, after ASM, a lot of research work was carried out based on hazy features. These features are extracted manually, and some are selected by automatic extraction methods. Many automatic feature extraction methods are based on artificial intelligence and its subbranches. He et al. [4] proposed Dark channel prior (DCP) to estimate the transmission map and atmospheric light of the hazy image. The hazy-free image is obtained by using ASM. DCP is computationally cost-effective but suffers from color deficiency. Whereas Zhu et al. [5] proposed color attenuation prior (CAP) in place of DCP for effective image dehazing without color loss.

The SID approaches are categorized into several methods in the literature as model-based (MB), data-driven (DD), prior-based (PB), and learning-based (LB).

As machine learning (ML) has advanced in the realm of image processing, numerous approaches based on ML with priors and statistical assumptions about picture data have already been suggested. Pandey et al. [6] proposed using PCA and a modified DCP to defog a single fog image. The algorithm takes foggy images and preprocesses them using principal component analysis. Following that, a fast global smoothing filter was used for additional enhancement, consuming less time and data while maintaining quality. On both synthetic and natural data sets, qualitative and quantitative analysis was performed.

With the introduction of CNN, image dehazing research changed its novelty. Many new methods were proposed based on CNN and the networks of CNN for feature extraction and reconstruction of hazy images. Liu et al. [7] used the CycleGAN network for unpaired fog and fog-free training images in multiple real-world foggy image datasets (MRFID). Z. Li et al. [8] provide a unique single picture dehazing technique that combines MB and DD approaches. MB methods are used to predict the T and A, which are subsequently improved using dual-scale GANs-based methodologies. The resulting method generates a neural augmentation that converges relatively quickly, whereas the analogous DD technique may not. The $T, A,$ and Koschmieder's laws are used to reconstruct haze-free photos. Meng et al. [9] proposed a two-stream CNN-based network to extract spatial information features and high-level semantic features for image dehazing. Mo et al. [10] have given DCA-CycleGAN, a GAN model that uses Dark Channel Attention (DCA) as input along with HI. The DCA is created using an unsupervised DCP. CNN-based methods give better results compared to traditional methods, but these methods require large datasets to train.

Combination-based method Zhao et al. [11] sought to combine the PB and LB techniques by breaking down the job into two subtasks: visibility restoration and realness enhancement. The dehazing framework (RefineDNet) employed the DCP to restore visibility in the first task. In the second task, it increases realism using adversarial learning and unpaired hazy and clear images by blending distinct dehazing outputs employing first-stage findings and an effective perceptual fusion technique. By dividing the task into subtasks training can be reduced and increase efficiency.

Decomposition-based method Hu et al. [12] suggested a three-step picture defogging approach for visual marine surveillance. In the first stage, a comprehensive scattering model (CSM) and a decomposition technique were applied. In the glow-shaped ambient lighting, a CSM was applied to create a fog image. A decomposition approach was utilized to remove the glow effect from the air light radiance and reconstruct a haze layer to provide the objects with consistent brightness. In the second stage, the transmission map was calculated using non-local haze lines, which were then utilized to limit the T to a tolerable level for the input haze image. Lastly, the lighting correction technique allowed the DH image to retain the input's natural illumination information. Li et al. [13] employed a residual-based deep CNN (RDBCNN). The RDBCNN was separated into two tasks: task one, a hazy picture, was used as input to train CNN to generate a T. The combination of the haze picture and T was utilized as input in the second task, and ResNet was employed to remove haze from the provided hazy image. The decomposition-based method reduces training by dividing the task into subtasks and training only the required and trainable models for subtasks.

The NHASM was created based on the heterogeneous atmospheric light estimate of haze photos. Wang et al. [14] introduced a completely NHASM using CNN that estimates the angular scattering coefficient (ASC), d, and A factor, with respective loss functions for the ASC being β-Loss and d estimating module D-Loss. Wang et al. [15] suggested the Front White Balance Network (FWB) network for colour shift correction using a NHASM that estimated A with the FWB-loss and estimated T using a CNN model for HFI recovery using the HFM recovery eq. (3). These methods [14] and [15] assume the atmospheric light is nonhomogeneous thus increasing the efficiency by estimating atmospheric light for each pixel.Cai et al. [16] given DehazeNet, which uses a CNN with a BReLU for ID.

Attention-based methods have proven to be more effective in SID. Chen et al. [20] presented a detail-enhanced attention block (DEAB) composed of detail-enhanced convolution (DEConv) and content-guided attention (CGA) to improve dehazing performance by boosting feature learning. Guo et al. [21] proposed a hybrid approach by combining a transformer and CNN encoder for effective extraction of image features and a CNN decoder for reconstruction of HIF. Revanth et al. [22] proposed a hybrid approach by combining ASM and generative models using fusion networks. The hybrid approaches are better in some cases with minimal training and computational cost when compared with traditional methods.

III. Proposed Method

The non-homogeneous hazy image formation model (NHHFM) has three steps. In the first step, as in [6], non-homogeneous atmospheric light is estimated using ML and DL-based networks called non-homogeneous light estimation network (NHLEN). A refined transmission map is estimated in the second step, followed by NHASM to recover the HFI in the third stage. As shown in fig. 1, the input haze image (HI) is passed through two networks, namely the WBEN explained in subsection 3.1, and the Global Atmospheric Light Estimation Network (GAEN) explained in subsection 3.2, to estimate global atmospheric light A. Refined transmission map estimation network (RTEN) is explained in subsection 3.3 is used to estimate the T of the HI. The HFI is recovered using A and T in the NHHFM as given in the eq. (6).

A. White Balance Error Network

The HI is the white-balanced error (WBE) image, which is passed through the WBEN; the WBEN corrects the WBE [17] and returns the corrected white balance image. The WBEN is inspired by [14] and [15], and the white balance error network is shown in fig. 1(a). WBEN takes a hazy image as input and extracts histogram features, from which the Compact PCA features are generated. The PCA features

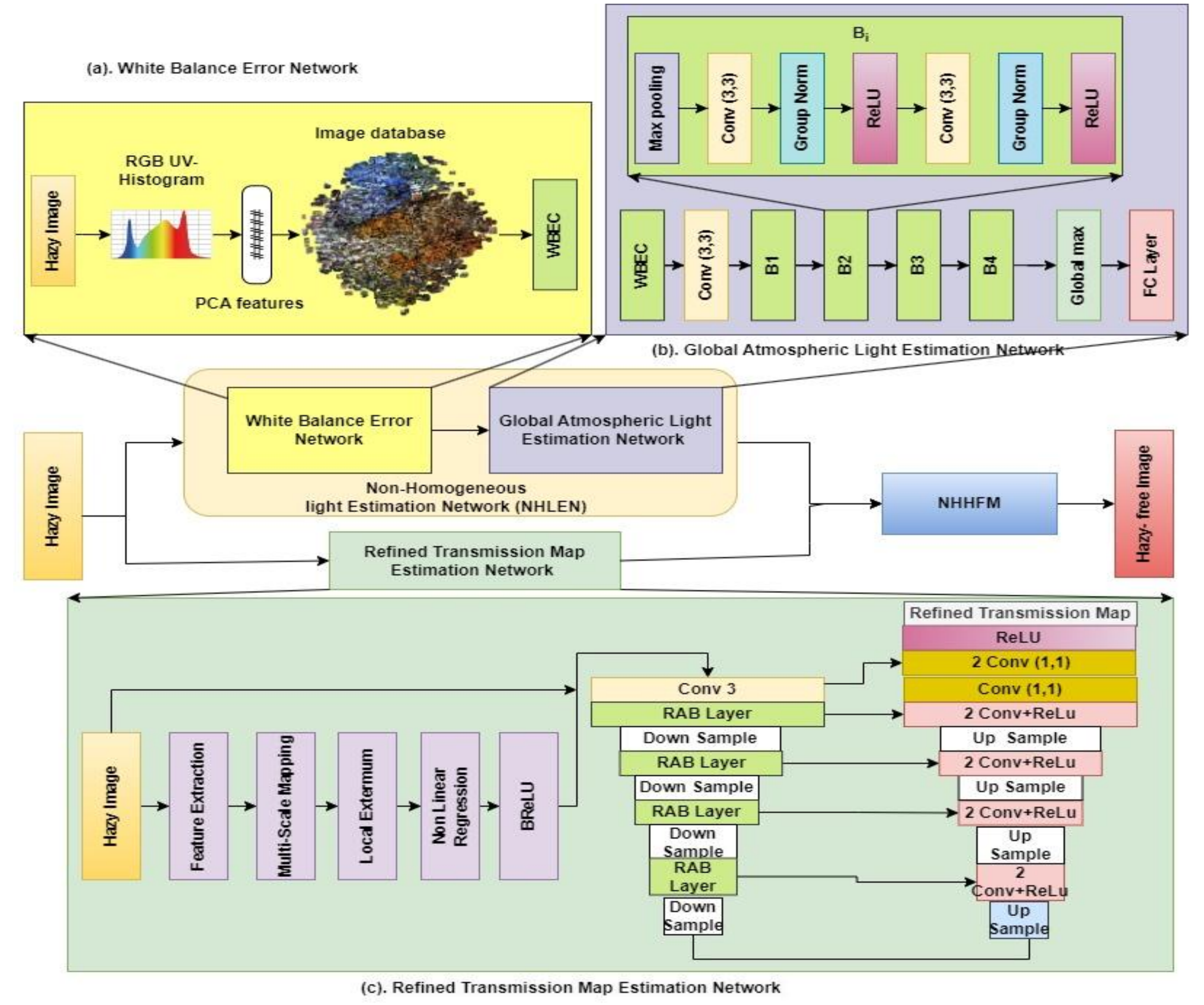

Fig. 1. Three step proposed method for NHASM based SID.

are given to the KNN algorithm to find similar images from the intrinsic set (Set 1) provided in the NUS dataset [17] and it corrects the WBE of the image, taking a group of similar images. Weighted mapping function M is computed from the k similar training examples $M_s^{(i)}$ using following eq. (7).

$$M = \propto_1 M_s^{(1)} + \propto_2 M_s^{(2)} \cdots + \propto_k M_s^{(s)} \tag{7}$$

Where $\propto$ is a radial basis function as weighting vector. Final correction matrix M is computed as a weighted linear combination of the correction matrices M_s

$$I_{corr} = M\Phi(I_{in}) \tag{8}$$

Where I_{corr} is corrected image and I_{in} is an incorrected image.

B. *Global atmospheric light estimation network (GAEN)*

Generally, the NHASM model has an atmospheric light factor for each pixel in the image, but as we corrected the WBE of the image, the atmospheric light factor for some pixel would get changed therefore it would be rational to use global atmospheric light (GA) instead of pixel level atmospheric light. The global atmospheric light is the image light factor; one value is for each channel and thus there are three image values in total. GA factor is calculated using a DCNN-based network called the Global Atmospheric Light Estimation Network (GAEN). The GAEN is shown in fig. 1(b).

The WBE-corrected (I_{corr}) image is sent to GAEN as input, and it returns a GA factor of three values as output. The GAEN is a DL-based network in which DCNN is used to construct the network. The network has seven layers: first, a CNN; the second, third, and fourth layers are conv-blocks (B_i); B_i has a series of max pooling, CNN, and group norm are present in each conv-block. The sixth layer is the global maximum layer, and the seventh layer is a fully connected layer for the GAEN.

The GAEN outputs a GA factor of three values; generally, many CNN-based networks [15], [16] give an atmospheric light map with the size of the input image. These atmospheric light map work at pixel-level, which are almost the same value for the entire channel of the image, i.e., three values for the three channels of the image. Hence, we have used a map that gives only three values of atmospheric light factor in order to make computation easier

C. *Refined transmission map estimation network (RTEN)*

The novelty of the NHHFM is the RTEN, which generates a refined transmission map without using a guided filter like traditional methods in [4], [5], [13], [16], and [19]. The RTEN is an end-to-end network that can be trained and used as an asset for many methods that require a refined transmission map for dehazing applications. RTEN is created by combing two networks [16] and [18] in series. RTEN is shown in fig. 1(c). The RTEN is constructed using DCNN, the HI is given as input to the network, and a refined transmission map (RTM) is returned as an output using attention mechanisms.

The Haze image is given as the input to the network; in the first step, the features are extracted using a feature extraction layer, and multi-scale mapping is performed on the features. The multi-scaled mapping output is subjected to local extremum and non-linear regression followed by BReLU [16] to generate a transmission map without fine details. The generated map is sent to a network that was designed based on U-Net [20]. The U-Net in RTEN has a series of Residual Attention Block (RAB)s with a down-sampling factor of 2, which are present in place of encoder, and up-sampling layers with a factor of 2, followed by CNN and ReLU layers that are present in place of decoders. RAB is the residual block in which a series of pre-processed features are residual with channel attention vectors; further, the channel features are extracted, and spatial max pooling is used to generate spatial attention maps. Skip connections are present between the RAB and CNN. Finally, the RTM is produced. The haze-free image is recovered using the haze image, global atmospheric light, and a refined transmission map by using eq. (6).

IV. EXPERIMENT & DISCUSSION

A. *Data-sets*

Indoor-HAZE [11], Outdoor-HAZE [13], and NR-Indoor are used for evaluating proposed method. by using the [11] has 35 HI images and ground truth images (GT). [13] has 45 HI with GT and NR-Indoor datasets with 1346 clean images and depth maps. Using the NR-indoor dataset, the A and T are generated using NHASM. The T is calculated based on eq.2. Transmission value is 0.2 to 0.8 and A value is 0.3 to 1.0 for one layer and 0 to 40% of A value for the remaining two layers. The haze images are created using eq. 4. Indoor-HAZE and Outdoor -HAZE are light haze image datasets whereas NR-Indoor is having light to heavy haze images.

B. *Experimental Setting*

The proposed method is implemented on the platform of Google Collaboratory (Google Colab), and the technique (proposed method) requires a 224 ×224 input size. The number of training epochs is 50, the batch size is 10, and the Adam optimizer has learning rates of 0.001, 0.9, and 0.999. The input image size of 224 ×224 is due to the fact that larger input images require more computational power, memory, and training time, making 224 ×224 the ideal input image size for image dehazing. The atmospheric light estimation network and refined transmission map estimation network are trained on the NR-Indoor dataset using the MSE loss function and hybrid loss function (HLF). HLF is a loss function that combines MSE and perceptual loss. Networks are tested on

Indoor-HAZE, Outdoor-HAZE and randomly selected images from the NR-Indoor dataset.

$$\mathrm{MSE}(\mathrm{I},\mathrm{O}) = \frac{\sum_{\mathrm{i,j}}[\mathrm{I(i,j)} - \mathrm{O(i,j)}]^2}{\mathrm{i} * \mathrm{j}} \tag{9}$$

$$\mathrm{PL}(\mathrm{I},\mathrm{O}) = \mathrm{MSE}(\mathrm{VGG(I)}, \mathrm{VGG(O)}) \tag{10}$$

$$\mathrm{HLF}(\mathrm{I},\mathrm{O}) = \mathrm{MSE}(\mathrm{I},\mathrm{O}) * \mu(\mathrm{PL}(\mathrm{I},\mathrm{O})) \tag{11}$$

Where I, O are the input and output images, VGG (Visual Geometry Group) is a pre trained network $VGG - 16$. i,j are the rows and columns of the image. μ is scalar (μ = 0.2) in gernal.

TABLE I
PERFORMANCE COMPARISON ON INDOOR-HAZE AND OUTDOOR-HAZE,

Method	INDOOR-HAZE		OUTDOOR-HAZE	
	PSNR	***SSIM***	***PSNR***	***SSIM***
DCP [4]	14.43	0.653	16.78	0.653
CAP [5]	12.24	0.596	16.08	0.596
RBDC [13]	27.69	0.327	27.58	0.548
FWB-NET [15]	-	-	19.7	0.763
DehazeNet [16]	25.93	0.493	**28.03**	0.493
EDN-GTM [19]	22.90	**0.827**	23.46	**0.819**
GMAN [23]	**27.72**	0.223	27.97	0.138
NHHFM (Proposed model)	27.63	0.516	27.82	0.460

TABLE II
PERFORMANCE COMPARISON ON NR-INDOOR

Method	NR -INDOOR	
	PSNR	***SSIM***
DCP [4]	16.08	0.663
CAP [5]	16.28	0.490
RBDC [13]	26.20	0.434
FWB-NET [15]	18.9	**0.794**
DehazeNet [16]	27.03	0.323
EDN-GTM [19]	20.24	0.717
GMAN [23]	14.17	0.587
NHHFM (Proposed model)	**28.39**	0.604

C. Results

The proposed method performance on Indoor-HAZE, Outdoor-HAZE, and NR-Indoor datasets to those of other methods like DCP [4], CAP [5], RBDC [13], FWB-NET [15], DehazeNet [16], EDN-GTM [19], and GMAN [23] are given in Table I and Table II. The methods are reimplemented and tested on the above-mentioned datasets. When compared to other methods with respect to PSNR and SSIM, In most cases, our results are better than others; however, in a few cases, like [23] and [13] in terms of PSNR and [19], [4] and [5] in terms of SSIM of the Indoor-HAZE dataset, [16] and [23] in terms of PSNR and [19], [15], [4], [5], [13], and [16] in terms of SSIM of the Outdoor-HAZE dataset, they perform better. But in the case of non-homogenous dense haze images (NR-INDOOR), our method always performs better than the other methods. In terms of PSNR and the third-best results in terms of SSIM So, we can say that, on average, the proposed method outperforms other methods.

V. CONCLUSION

A unique DCNN-based approach for NHASM for SID is proposed in this study. The suggested approach takes an HI as an input and outputs an HFI. There are three phases of the proposed Method. The WBEN, in conjunction with GAEN, is utilized in the initial stage to determine GA. The RTM is estimated in the second stage utilizing the refined transmission map estimation network (RTEN) and the NHASM model. The last HFI was retrieved. The WBEN uses KNN on the Intrinsic Set 1 dataset, whereas GAEN and RTEN are trained on the NR-indoor dataset using MSE and HLF as loss functions. In terms of PSNR and SSIM metrics, testing on benchmark data sets demonstrates that the proposed method performs better than the majority of conventional and DL-based methods. In the future work, an NHASM with a residual recurrence model may be investigated.

REFERENCES

[1] L. R. Bissonnette, ‘‘Imaging through fog and rain,’’ Opt. Eng., vol. 31, no. 5, pp. 1045–1052, May 1992.

[2] J. P. Oakley and B. L. Satherley, ‘‘Improving image quality in poor visibility conditions using a physical model for contrast degradation,’’ IEEE Trans. Image Process., vol. 7, no. 2, pp167–179, Feb. 1998.

[3] S. G. Narasimhan and S. K. Nayar, ‘‘Contrast restoration of weather degraded images,’’ IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, no. 6, pp. 713–724, Jun. 2003.

[4] He, Kaiming, Jian Sun, and Xiaoou Tang. "Single image haze removal using dark channel prior." IEEE transactions on pattern analysis and machine intelligence 33, no. 12 (2010): 2341-2353.

[5] Zhu, Qingsong, Jiaming Mai, and Ling Shao. "A fast single image haze removal algorithm using color attenuation prior." IEEE transactions on image processing 24, no. 11 (2015): 3522-3533.

[6] Pandey, Pooja, Rashmi Gupta, and Nidhi Goel. "A fast and effective vision enhancement method for single foggy image." Engineering Science and Technology, an International Journal 24, no. 6 (2021): 1478-1489.

[7] Liu, Wei, Xianxu Hou, Jiang Duan, and Guoping Qiu. "End-to-end single image fog removal using enhanced cycle consistent adversarial networks." IEEE Transactions on Image Processing 29 (2020): 7819-7833.

[8] Z. Li, C. Zheng, H. Shu and S. Wu, "Dual-Scale Single Image Dehazing via Neural Augmentation," in IEEE Transactions on Image Processing, vol. 31, pp. 6213-6223, 2022, doi: 10.1109/TIP.2022.3207571.

[9] Meng, Jun, Yuanyuan Li, HuaHua Liang, and You Ma. "Single-image dehazing based on two-stream convolutional neural network." Journal of Artificial Intelligence and Technology 2, no. 3 (2022): 100-110.

[10] Mo, Yaozong, Chaofeng Li, Yuhui Zheng, and Xiaojun Wu. "DCA-CycleGAN: Unsupervised single image dehazing using dark channel attention optimized CycleGAN." Journal of Visual Communication and Image Representation 82 (2022): 103431.

[11] Zhao, Shiyu, Lin Zhang, Ying Shen, and Yicong Zhou. "RefineDNet: a weakly supervised refinement framework for single image dehazing." IEEE Transactions on Image Processing 30 (2021): 3391-3404.

[12] Hu, Hai-Miao, Qiang Guo, Jin Zheng, Hanzi Wang, and Bo Li. "Single image defogging based on illumination decomposition for visual maritime surveillance." IEEE Transactions on Image Processing 28, no. 6 (2019): 2882-2897.

[13] Li, Jinjiang, Guihui Li, and Hui Fan. "Image dehazing using residual-based deep CNN." IEEE Access 6 (2018): 26831-26842.

[14] Wang, Cong, Yan Huang, Yuexian Zou, and Yong Xu. ”Fully Non-Homogeneous Atmospheric Scattering Modeling with Convolutional Neural Networks for Single Image Dehazing.” arXiv preprint arXiv:2108.11292 (2021).

[15] Wang, Cong, Yan Huang, Yuexian Zou, and Yong Xu. ”FWB-Net: front white balance network for color shift correction in single image dehazing via atmospheric light estimation.” In ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 2040-2044. IEEE, 2021

[16] Cai, Bolun, Xiangmin Xu, Kui Jia, Chunmei Qing, and Dacheng Tao. ”Dehazenet: An end-to-end system for single image haze removal.” IEEE Transactions on Image Processing 25, no. 11 (2016): 5187-5198.

[17] Afifi, Mahmoud, Brian Price, Scott Cohen, and Michael S. Brown. "When color constancy goes wrong: Correcting improperly white-balanced images." In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pp. 1535-1544. 2019.

[18] Liao, Yinghong, Bin Qiu, Zhuo Su, Ruomei Wang, and Xiangjian He. "Learning transmission filtering network for image-based Pm2. 5 estimation." In 2019 IEEE International Conference on Multimedia and Expo (ICME), pp. 266-271. IEEE, 2019.

[19] Tran, Le-Anh, Seokyong Moon, and Dong-Chul Park. ”A novel encoderdecoder network with guided transmission map for single image dehazing.” arXiv preprint arXiv:2202.04757 (2022).

[20] Chen, Zixuan, Zewei He, and Zhe-Ming Lu. "DEA-Net: Single image dehazing based on detail-enhanced convolution and content-guided attention." arXiv preprint arXiv:2301.04805 (2023).

[21] Guo, Chun-Le, Qixin Yan, Saeed Anwar, Runmin Cong, Wenqi Ren, and Chongyi Li. "Image dehazing transformer with transmission-aware 3D position embedding." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 5812-5820. 2022.

[22] Revanth, Banala, Sanjay K. Dwivedi, and Manoj Kumar. "A Framework For Single Image Dehazing Using DWT Based Cross Bilateral Filter Fusion of Generative and ASM Models." In 2022 2nd International Conference on Innovative Sustainable Computational Technologies (CISCT), pp. 1-6. IEEE, 2022.

Liu, Zheng, Botao Xiao, Muhammad Alrabeiah, Keyan Wang, and Jun Chen. "Generic model-agnostic convolutional neural network for single image dehazing." arXiv preprint arXiv:1810.02862 (2018).