DHD-Net: A Novel Deep-Learning-based Dehazing Network

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***Abstract*—Eliminating haze interference in images is still a challenging problem. In this paper, we consider more systematically the physical hazing mechanisms, combined with deep learning, propose a new end-to-end dehazing network called DHD-Net. For physical hazing mechanisms, we fuse the global atmosphere light, transmission maps, and the atmospheric scattering model for dehazing. For the estimation of global atmosphere light, We propose a deep learning-based haze density estimation algorithm (DL-HDE). We establish a new dataset, of which each data item consists of the hazy image, the transmission map, the haze-free image, and the dense-haze area mask. Our experimental results demonstrate that our proposed DHD-Net has better dehazing performance than state-of-the-art algorithms.**

***Index Terms*—Dehazing, Haze Density, Atmospheric Scattering Model, Deep Learning, Image Processing**

I. Introduction

The imaging process is extremely vulnerable to interferences from atmospheric scattering and absorption, especially in severe haze weather. The collected images are easily affected, and the loss of image feature information caused by haze obstructs subsequent image processing tasks. Eliminating haze interference is still a challenging problem.

Early image dehazing algorithms can be mainly divided into image enhancement-based (IEM) [1]–[3] and physical model-based (PMM) methods [4]–[15]. Image enhancement-based methods can achieve better visual results such as increasing the contrast of images [3]. However, these methods do not consider image degradation, so they tend to lose image details during processing. On the other hand, the physical-model-based methods study the causes of the degradation of hazy images: by analyzing and summarizing the laws of the weakening process of light, the light attenuation model is constructed, and then the restored model is used to compensate for the distorted parts of the scene and achieve dehazing. Compared with IEMs, PMMs can perform targeted reduction according to different reasons of image degradation and the restored information is closer to the original haze-free image, hence better dehazing results can be obtained. Most of PMMs rely on atmospheric scattering models. The key of these models is to obtain accurate global atmosphere light value and transmission map, which is an *ill-posed* problem [7].

In order to address the issues caused the ill-posed problem, researchers proposed to include prior knowledge, such as using prior knowledge to help estimating the transmission map, and using a fixed rule of thumb (i.e., based on experience) to estimate global atmosphere light. For example, the DCP proposed by He et al. [4] and the prior knowledge of haze lines proposed by Bermen et al. [6]. However, these methods have more scene restrictions and pay insufficient attention to the estimation of the global atmosphere light. Recently deep learning (DL) starts being applied in dehazing, e.g., FFA-Net proposed by Qin et al. [18] and DCPDN proposed by Zhang et al. [9]. Compared with early dehazing methods, the DL-based algorithms are more robust and have better performance.

In this paper, based on deep learning, we associate transmission maps, the global atmosphere light, and hazy images, and use the atmospheric scattering model for dehazing. As mentioned above, most existing methods attach more importance to the estimation of the transmission map and consider less the estimation of global atmosphere light during the dehazing process. Indeed, *dense haze areas* (DHAs) are important for the estimation of global atmosphere light [15]. We propose an DL-based haze density estimation algorithm (DL-HDE), which uses deep learning methods to segment DHAs and further divide the global atmosphere light candidate area according to the characteristics of the haze to estimate the global atmosphere light. We then propose a new end-to-end dehazing network based on DL-HDE (DHD-Net). Because the image haze is the depth-dependent noise and nonuniform, we use the Pyramid Densely Connected Neural Network [9] to estimate the transmission map in DHD-Net. Pyramid Densely Connected Neural Network can effectively estimate features on transmission map and preserve global information [20]. Finally, the atmospheric scattering model is used in DHD-Net to fuse the transmission map, the global atmosphere light and the hazy image to remove the haze. In this way, DHD-Net considers more systematically the physical hazing mechanisms, therefore combined with DL, can achieve better dehazing performance. Last but not least, in order for the validation of our new dehazing network, we establish a new dataset, of

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which each data item consists of the hazy image, the transmission map, the haze-free image, and the dense-haze area mask. We perform comprehensively comparative experiments with state-of-the-art algorithms. Our experiments show that the proposed DHD-Net performs better w.r.t. the commonly used *Structural Similarity Index* (SSIM) and *Peak Signal to Noise Ratio* (PSNR). DHD-Net avoids image distortion and chromatic aberration, and retains more edge information. In summary, our contributions are listed as follows:

- We propose a new DL-based algorithm for estimating the global atmosphere light called DL-HDE.
- Based on DL-HDE, we propose a new end-to-end dehazing network called DHD-Net. This new network considers more systematically the physical hazing mechanisms and achieves better dehazing performance than state-of-the-art algorithms.
- We establish a new dataset, of which each data item consists of the hazy image, the transmission map, the (ground-truth) haze-free image, and the DHA mask.

II. Related Work

In recent years, dehazing methods can be roughly divided into two types, 1) dehazing algorithms based on prior knowledge; and 2) DL-based dehazing algorithms.

The representative methods in prior knowledge-based dehazing algorithms such as He et al. [4] proposed to use the Dark Channel Prior (DCP) to dehaze. However, the time and space complexity of this method is high, and insufficient consideration is given to the estimation of the global atmosphere light, the result of dehazing may loss details, and some areas appear severely distorted. Zhu et al. [5] proposed, in addition to DCP, to use the color attenuation prior knowledge based on the relationship between haze density and scene depth, and build a linear regression model to estimate scene depth using brightness and saturation, finally get the transmission map to dehaze. Berman et al. [6] proposed the prior knowledge of haze lines, in which used the haze lines of global pixels is used to estimate the transmission map. This method is more robust, but it is diffcult to predict the haze lines when the global illumination is much stronger than the brightness.

In order to achieve better dehazing effect and improve the robustness of dehazing algorithms, DL starts being adapted in dehazing recently. There are mainly two types of DL-based dehazing algorithms: 1) to generate the haze-free image directly [16]–[19].By learning the paired hazy images and haze-free images, the deep learning network can directly estimate the haze-free image, such as Conditional generative adversarial network (cGAN) for dehazing proposed by Li et al. [16], gated context aggregation network (GCANet) by Chen et al. [17], and Feature fusion attention network (FFA-Net) proposed by Qin et al. [18]; 2) to using DL to estimate the coefficients in the physical models and get the haze-free image [7]–[9], [12], [14], such as DehazeNet [7] by Cai et al., An allin-one network (AOD-Net) by Li et al. [8] and Densely connected pyramid dehazing network (DCPDN) by Zhang et al. [9].

Based on these existing algorithms, we can see that it is important for dehazing algorithms to accurately estimate the transmission map and global atmosphere light.

A. Methods for transmission map estimation

The methods for estimating transmission map mainly have two categories: 1) methods based on prior knowledge; and 2) methods based on deep learning. As mentioned in Section I, methods based on prior knowledge include DCP [4], color attenuation [5], and haze lines [6]. In addition, Fattal et al. [13] proposed a dehazing algorithm based on color information, which estimates the transmission map through independent component analysis. But it is not applicable to colorless dense-hazy scenes and gray-scale images. In general, methods based on prior knowledge have more scene limitations, and methods considering only one perspective of prior knowledge, e.g., color attenuation, cannot effectively adapt to highly varied hazy scenarios.

Deep learning-based methods include DehazeNet proposed by Cai et al. [7]. DehazeNet builds a convolutional neural network (CNN), which takes hazy images as input and produces transmission maps as output. Ren et al. [14] improved CNN and proposed a multiscale CNN to estimate the transmission map, which can extract multi-scale features. To include global structural information, Zhang et al. [9] designed a densely connected encoder-decoder structure with multilevel pyramid pooling model to estimate the transmission map.

B. Methods for global atmosphere light estimation

Previous dehazing works have not paid enough attention to the estimation of global atmosphere light. For example, in DCP [4], a fixed rule of thumb is used to estimate the global atmosphere light, which extracts the brightness value corresponding to the top 0.1% of the brightest gray position in the black channel map as the global atmosphere light. In particular, this method estimates incorrectly due to noises caused by the light from bright objects such as table lamps.

Afterwards, researchers found that an accurate estimation of global atmosphere light is more conducive to dehazing. For example, AOD-Net proposed by Li et al. [8] unified the transmission map and global atmosphere light into a variable, and estimated this variable through the network. Zhang et al. [9] proposed to use U-Net to directly learn global atmosphere light in the hazy image. We propose to identify DHAs in the process of estimating the global atmosphere light because intuitively this way we include more prior knowledge on physical hazing mechanisms. Experiments show that our method outperform mentioned existing methods.

Kim et al. [11] proposed the idea of establishing a global atmosphere light candidate area through a quad-tree search method and a scoring mechanism. However this method still cannot overcome the noises by bright objects when the global atmosphere light candidate area contains bright objects. According to the relationship between haze density and global atmosphere light, Ju et al. [15] proposed an algorithm to screen the candidate area of global atmosphere light through

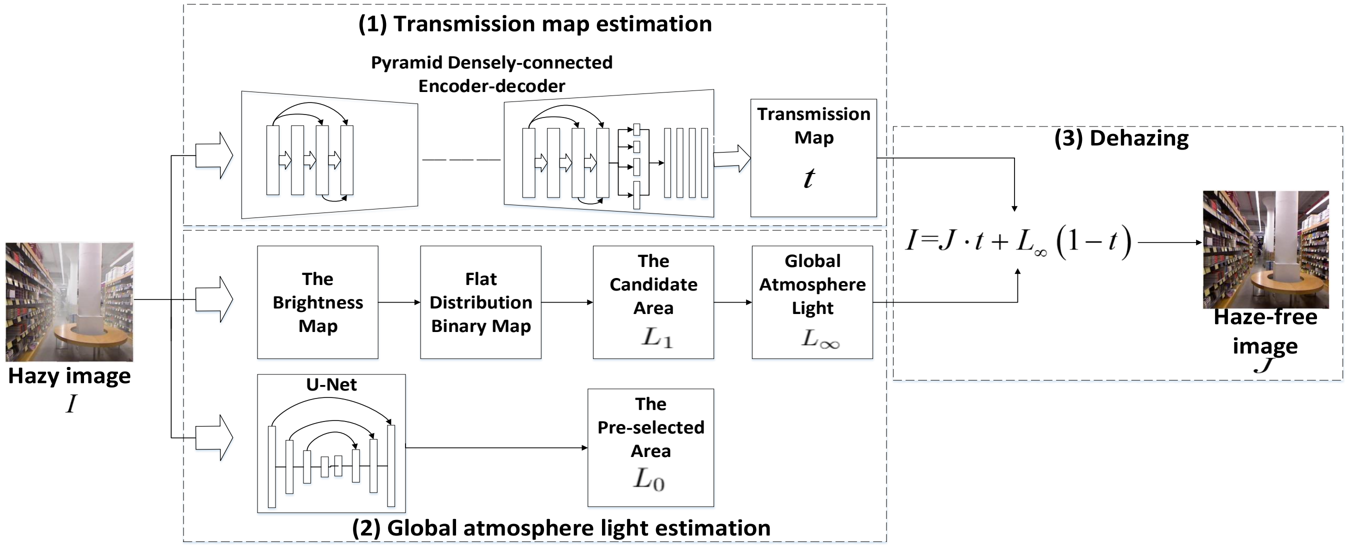


Fig. 1: The architecture of DHD-Net.

the physical properties of haze, which can avoid the influence of bright objects and noises caused by them. This algorithm relies on the accurate positioning of the DHA, for which they applied Fuzzy c-means (FCM). However, FCM did not take into account the spatial information of the image, therefore it is very sensitive to noises and uneven gray distributions. And FCM is randomly initialized, so the clustering results could be biased. To overcome this problem, we propose to use deep learning methods to segment and identify the DHA. Experments show that our method is more robust in estimating the global atmosphere light.

III. Proposed Network

Our end-to-end dehazing network, DHD-Net, is depicted in Fig. 1. The network mainly consists of 3 parts: 1) Transmission map estimating using Pyramid Densely Connected Neural Network; 2) Global atmosphere light estimation; and 3) Dehazing using the atmospheric scattering model.

A. Transmission map estimation based on Pyramid Densely Connected Neural Network

This structure is a tightly connected encoder-decoder structure, and each layer consists of a number of dense blocks. Because the deep features of the image need to be extracted for estimating the transmission map, such a structure can maximize the preservation of feature information in each layer. In addition, this neural network uses a multi-level pyramid pooling block so that the information in each layer can be directly used to estimate the transmission map. In this way, the final result has "global" feature information from objects of different scales. The structure of Pyramid Densely Connected Neural Network is depicted in the Fig. 2.

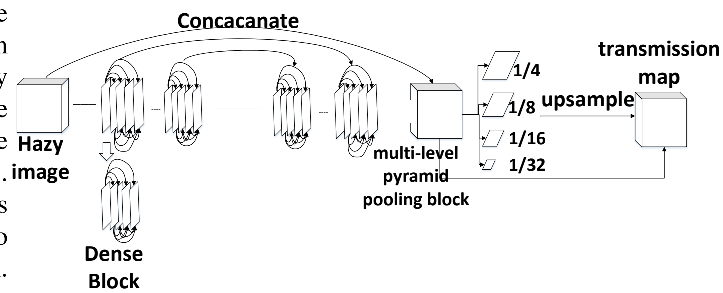


Fig. 2: The structure of Pyramid Densely Connected Neural Network (adapted from Fig. 3 in [9]).

B. Global atmosphere light estimation based on our proposed method

As mentioned earlier, haze density is important in the estimation of the global atmosphere light. We propose a new haze density estimation algorithm, DL-HDE, to segment DHAs and further divide the global atmosphere light candidate area according to the characteristics of the haze to estimate the global atmosphere light. For the segmentation, we use the U-shaped CNN, a.k.a. U-Net [21]. The haze information is often closely related to the depth information in the image. We use this information to generate DHA mask map, which is a critical component in the training dataset. For the details of generating DHA mask map, please refer to Section IV-A. U-Net's unique U-shaped symmetrical structure design integrates low-dimensional and high-dimensional features in the network, which makes the resolution of the output layer consistent. In this way, a higher precise segmentation on hazy image can be obtained.

The encoder structure of U-Net can down-sample the input image, so as to obtain a series of features about the haze density, which are smaller in size than the original image. Downsampling can also increase the size of the receptive field for obtaining global illumination information, which is important for the estimation of the haze density. The decoder in U-Net is used to guide the encoder to select relatively important feature information, and restore the abstracted features to the size of the original image, and finally get the segmented DHA of the hazy image. The process of DL-HDE is shown in Fig. 3.

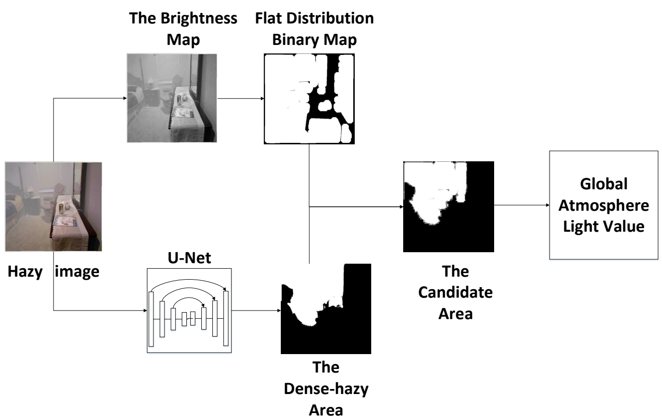


Fig. 3: The process of global atmosphere light value estimation.

The segmented DHA is used as the global atmosphere light pre-selection area L_0, and then the brightness image of the hazy image is processed to divide the flat area and texture area of the hazy image. According to the flatness characteristics of the DHA, the candidate area L_1 of the global atmosphere light is further filtered out in L_0. Finally, the maximum brightness value in L_1 is used as the global atmosphere light value. If the segmented L_1 is empty, i.e. there are no pixels in L_1, the average value of the first 30% of the larger brightness in L_0 is used as the global atmosphere light value.

C. Dehazing

Our algorithm follows the physical hazing mechanisms and uses the atmospheric scattering model for dehazing. The mathematical expression of the atmospheric scattering model is as follows:

$$I = J \cdot t + L_\infty(1-t) \tag{1}$$

where I is observed hazy image, J is the expected haze-free image, L_∞ is the global atmosphere light and t is the transmission map. This shows the key to dehazing is to estimate the global atmosphere light L_∞ and transmission map t from the hazy image.

In order to achieve an end-to-end network, we embed the global atmosphere light value A and the atmospheric scattering model (1) into the model. The hazy image I is input to the Pyramid Densely Connected Neural Network for training to estimate the transmission map t. Similar to existing works, we assume that the global atmosphere light with a hazy image is uniform, i.e. the global atmosphere light value A is spread out according to the size of the transmission map t. In this way, every pixel in the global atmosphere light map L_∞ is the same, and its value is A. Finally, the transmission map t, the global atmosphere light map L_∞, and the hazy image I are input into (1) to produce a haze-free image J.

D. Loss Functions

a) Loss for segmenting the DHA Using U-Net: For image binary classification and segmentation, BCE loss is widely used. But BCE loss performs poorly for imbalanced data, which is the case for segmenting DHAs. Dice loss [22] performs well for unbalanced data but it is unfavorable for small objects [23] and the convergence could be unstable in some cases [24]. Here we use an integrated BCE+Dice loss function for DHA segmentation, formulated as:

$$\begin{aligned} L_{BCE+Dice} &= L_{BCE} - \log(1. - L_{Dice}) \\ &= -g \cdot \log g_{pred} - (1-g)\log(1-g) \\ &- \log(1. - (1 - \frac{\sum_{n=1}^{N} g \cdot g_{pred} + \epsilon}{\sum_{n=1}^{N} g + g_{pred} + \epsilon} \\ &- \frac{\sum_{n=1}^{N}(1-g)(1-g_{pred}) + \epsilon}{\sum_{n=1}^{N} 2 - g - g_{pred} + \epsilon})) \end{aligned} \tag{2}$$

where g is the true DHA with hazy image, and g_{pred} is the DHA segmented by U-Net from the hazy image, N is the number of channels of the image.

b) Loss for estimating transmission map using Pyramid Densely Connected Neural Network: In DCPDN [9], an edge-preserving loss function was proposed to train the Pyramid Densely Connected Neural Network. The edge-preserving loss function consists of 3 parts: $L2$ loss, two-directional gradient loss, and feature edge loss. The feature edge loss is calculated based on shallow features extracted from VGG-16.

In our network, we replace the $L2$ loss with the $L1$ loss in the edge-preserving loss function. Although the $L2$ loss converges faster and is more widely used in dehazing, some researches [25] pointed out that the $L1$ loss is more robust to outliers, has smaller gradient changes, and performs better in terms of SSIM metrics. The formula for the loss function L_t for estimating transmission map in DHD-Net is:

$$L_t = \lambda_{l_1} L_{l_1} + \lambda_g L_g + \lambda_f L_f \tag{3}$$

where L_{l_1} stands for the $L1$ loss, L_g stands for the two-directional gradient loss, and L_f stands for the feature edge loss. λ_{l_1}, λ_g and λ_f are weight coefficients.

c) Overall Loss: We train the our DHD-Net using the overall loss function as follows:

$$L = L_t + L_{BCE+Dice} + L_d \tag{4}$$

where L_t and $L_{BCE+Dice}$ are the same as above. L_d, using $L1$ loss function, represents the dehazing loss, which calculates the loss between the output and the ground-truth haze-free images.

E. Training

Training of DHD-Net is divided into two steps. The first step is to 1) segment the DHA in the hazy image, then 2) estimate the global atmosphere light value. The second step is to 1) estimate the transmission map by training the Pyramid Densely Connected Neural Network model; 2) construct the global atmosphere light map by spreading out the global atmosphere light value according to the size of the transmission map; 3) input the transmission map and the global atmosphere light map into the atmospheric scattering model to produce the haze-free image.

IV. EXPERIMENTS

We perform experiments on both synthetic and real-world datasets to verify the effectiveness of our proposed DHD-Net. We compare our DHD-Net with four state-of-the-art methods: DCP [1] (He CVPR'09), AOD-Net [8] (Li ICCV'17), DCPDN [9] (Zhang CVPR'18), and GCANet [5] (Chen WACV'19). We use SSIM and PSNR to evaluate the dehazing performance.

A. Dataset and Configurations

a) Dataset: DCPDN [9] proposed a dehazing dataset named $TrainA$, of which one data item consists of 4 parts: 1) Hazy image, 2) Haze-free image, 3) Transmission map, and 4) Global atmosphere light map. The dataset $TrainA$ contains 3000 synthetic data items and 1000 real-world data items randomly selected from the NYU-depth2 dataset. These 3000 items are synthesized based on (1), randomly selected from global atmosphere light coefficients L_∞ ranging from 0.5 to 1 and attenuation coefficient β ranging from 0.4 to 1.6.

Our dataset, named $TrainD$, is constructed based on $TrainA$. For one data item, we keep the hazy image, haze-free image, and the transmission map and discard the global atmosphere light map [1]. In addition, we generate a DHA mask map corresponding to the hazy image. In summary, one data item in our dataset $TrainD$ consists of 1) Hazy image; 2) Haze-free image; 3) Transmission map; and 4) DHA Mask map.

In order to generate the DHA mask map, we obtain the corresponding scene depth map d through the transmission map according to the assumption that when the global atmosphere light value is constant in a single image, the relationship between the transmission map and the scene depth map can be expressed as:

$$t = e^{-\beta \times d} \tag{5}$$

where t is the transmission map, β is the attenuation coefficient of the atmosphere and d is the scene depth map. Then we estimate the quantification map of haze density D based on a linear model defined by image-based brightness feature distribution and texture feature distribution. The linear model can be expressed as:

$$d \propto D = Q_L - \alpha \cdot Q_T \tag{6}$$

where D is the quantification map of haze density, d represents the scene depth map. Q_L is the brightness feature distribution of the image and Q_T is the texture feature distribution of the image. α is the weight coefficient, represents the degree of influence of texture features on the haze density. In the model, Q_L and Q_T can be expressed by the local brightness mean and the "adjusted" local gradient mean, as shown in the following formula:

$$\begin{cases} Q_L(m) = \frac{1}{|\omega|} \cdot \sum\limits_{n \in \omega(m)} L_I(n) \\ Q_T(m) = \frac{1}{|\omega|} \cdot \sum\limits_{n \in \omega(m)} |\nabla I(n)| \end{cases} \tag{7}$$

where $\omega(m)$ represents the neighborhood centered on the pixel index m, $|\omega|$ is the number of pixels in the neighborhood, L_I and ∇I are the brightness map and gradient map of the hazy image I, respectively.

Afterwards, we use the guided filter to perform edge-preserving smoothing on quantification map of haze density D. Finally, according to the prior knowledge [15] that the larger the value in the quantification map of haze density D, the denser the haze, we first divide the area with larger quantization values in D, and further based on the scene depth map d, continuously divide the areas with deep quantization values as the DHA in the hazy image, and make the mask map.

We establish a testset $TestD$ with 400 real-world data items selected from the NYU-depth2 dataset. We ensure that all test data items are not in the training set $TrainD$. We use indexes of SSIM and PSNR to evaluate the dehazing effect on $TestD$.

b) Configurations: In the process of training for DHA segmentation, we adopt the SGD optimizer, adjust the learning rate to 0.001, and set the batch size to 10. When training the dehazing model, we set the parameters $\lambda_{l_1} = 1$, $\lambda_g = 2$, and $\lambda_f = 2$ in the edge-preserving loss function to predict the estimated transmission map, and using the Adam optimizer, seting the batch size to 1. The training samples size is set to 512×512. During the training of the dehazing model, the global atmosphere light map with a size of 512×512 and a number of channels of 3, is input to the atmospheric scattering model. We use the PyTorch framework to implement our network and an RTX 2080Ti GPU to run our experiments.

B. Experiment on segmenting DHA in hazy images

We compare our DL-HDE algorithm with FCM and the Full Connected Network (FCN)[2] [26], using the Dice coefficient as the evaluation index. The experiment results on $TestD$ are shown in Table I and the DHA mask maps output by the 3 algorithms are shown in Fig. 4 along with the hazy image and the ground-truth mask map.

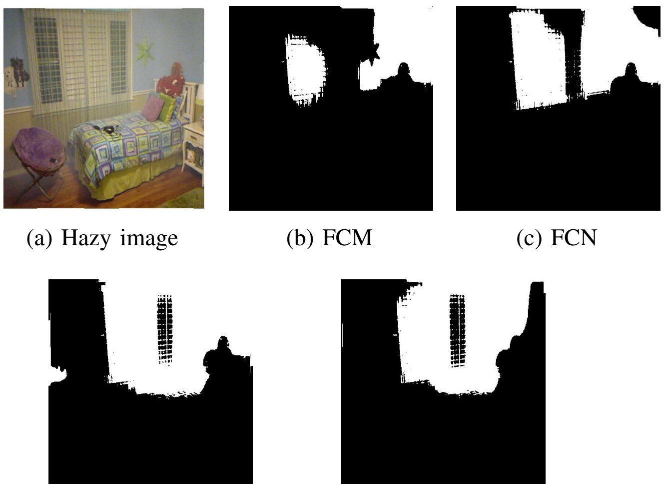
[1]Recall that we construct the global atmosphere light map by spreading out the global atmosphere light value according to the size of the transmission map

[2]A commonly-used DL network for image segmentation tasks.

TABLE I: Comparisons on DHA Segmentation

	FCM	FCN	DL-HDE
Mask image ↑	0.6693	0.7288	**0.7902**

In Table I, we can see that DL-HDE performs better than FCM and FCN in terms of the Dice coefficient in segmenting DHA for hazy images. In Fig. 4, we can see that the mask maps segmented by DL-HDE is closer to the ground-truth, and FCM and FCN cannot segment the DHA stably, there are missing areas, which will have a negative impact on the subsequent dehazing process.



(a) Hazy image (b) FCM (c) FCN

(d) DL-HDE (e) Ground-truth Mask Map

Fig. 4: The Results of DHA Mask Map Segmentation.

C. Comparisons on Dehazing

We compare our dehazing network, DHD-Net, with 4 state-of-the-art dehazing networks, namely DCP, AOD-Net, DCPDN and GCANet. We use SSIM and PSNR as the evaluation indexes.The SSIM and PSNR results on $TestD$ are shown in Table II.It can be seen that the SSIM and PSNR results of DHD-Net is the highest, i.e. the dehazing performance of DHD-Net on $TestD$ is the best.

The haze-free images output by all compared methods are shown in Fig. 5. There is almost no haze in the DCP's dehazed image, color aberration and distortion still occur in the dehazed image; AOD-Net is not thorough in dehazing the image with bright objects, and some details are lost. Although the image after dehazing with DCPDN is restored to global clarity, there are still small haze clusters in the dehazed image; the overall dehazing effect of GCANet is good, but ghosting and distortion still occur at the edges of the dehazed image, and not very good for cases with dense haze areas. Our DHD-Net preserves more detailed information while ensuring that the dehazed image contains no distortion or chromatic aberration. And the edge processing in DHD-Net is more stable. In addition, we observe that DHD-Net is more robust across different hazy images with different haze density levels.

V. CONCLUSION

In this paper, we proposed a new deep-learning-based end-to-end dehazing network called DHD-Net, considering more systematically the prior knowledge on hazing. We established a new dataset and validated that our proposed DHD-Net has better dehazing performance than state-of-the-art algorithms. In future work, we will further explore different scenarios for the atmospheric scattering model with different deep learning facilities. In addition, we will apply our dehazing network in more categories of hazy images.

REFERENCES

[1] J. Yu, D.P. Li, and Q.M. Liao, "Color constancy-based visibility enhancement of color images in low-light conditions." Acta Automatica Sinica, 37(8): 923-931. 2011.

[2] J.Q. Li, C.H. Yang, H.Q. Zhu, B.F. Cao, and J.P. Liu, "A new bubble image enhancement algorithm based on improved directionlet transform." Journal of Central South University (Science and Technology), 44(3): 1030-1036. 2013.

[3] R. Tan, "Visibility in Bad Weather from a Single Image." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2008), 2008.

[4] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior", IEEE transactions on pattern analysis and machine intelligence, 33(12):2341–2353. 2011.

[5] Q. Zhu, J. Mai, and L. Shao, "A fast single image haze removal algorithm using color attenuation prior." IEEE transactions on Image Processing, 24(11):3522–3533. 2015.

[6] D. Berman, S. Avidan, et al., "Non-local image dehazing."In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2016), pp.1674–1682. 2016.

[7] B. Cai, X. Xu, K. Jia, C. Qing, and D. Tao, "Dehazenet: An end-to-end system for single image haze removal." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2016), pp.25(11). 2016.

[8] B. Li, X. Peng, Z. Wang, J. Xu, and D. Feng, "An all-in-one network for dehazing and beyond." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2017), 2017.

[9] H. Zhang and V. M. Patel, "Densely connected pyramid dehazing network." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2018), 2018.

[10] X. Fu, Y. Sun, M. Liwang, Y. Huang, X.P. Zhang, and X. Ding, "A novel retinex based approach for image enhancement with illumination adjustment." In IEEE Conference on Acoustics. 2014.

[11] J.H. Kim, W.D. Jang, J.Y. Sim, and C.S. Kim."Optimized contrast enhancement for real-time image and video dehazing." Journal of Visual Communication Image Representation, pp.24(3):410-425. 2013.

[12] K. Tang, J. Yang, and J. Wang, "Investigating haze-relevant features in a learning framework for image dehazing." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2014), 2014.

[13] R. Fattal, "Dehazing using color-lines." ACM Transactions on Graphics, pp.34:1-14. 2014.

[14] W. Ren, S. Liu, H. Zhang, J. Pan, X. Cao, and M.H. Yang, "Single image dehazing via multi-scale convolutional neural networks." European Conference on Computer Vision (ECCV 2016), pp.154–169. Springer. 2016.

[15] M. Ju, D. Zhang, and Y. Ji, "Image Haze Removal Algorithm Based on Haze Thickness Estimation." Acta Automatica Sinica. 2016.

[16] R. Li, J. Pan, Z. Li, and J. Tang, "Single image dehazing via conditional generative adversarial network." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2018), 2018.

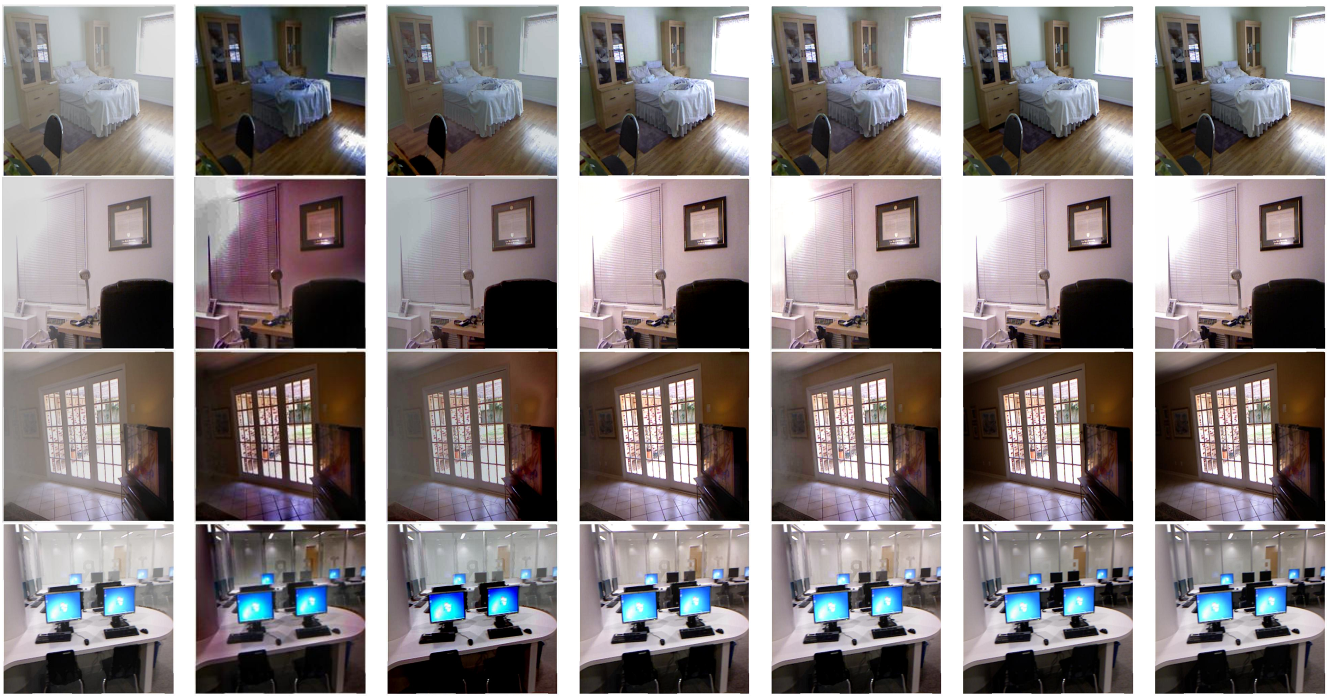
[17] D. Chen, M. He, Q. Fan, J. Liao *et al.*, "Gated Context Aggregation Network for Image Dehazing and Deraining." Winter Conference on Applications of Computer Vision. 2019.

[18] X. Qin, Z. Wang, Y. Bai and H. Jia, "FFA-Net: Feature fusion attention network for single image dehazing." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2020), 2020. In press.

[19] Y. Qu, Y. Chen, J. Huang, and Y. Xie, "Enhanced pix2pix dehazing network." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2019), 2019.

TABLE II: Comparison results on $TestD$

	DCP	AOD-Net	GCANet	DCPDN	DHD-Net
SSIM ↑	0.8642	0.8842	0.9133	0.9560	**0.9757**
PSNR ↑	17.7267	18.8693	24.8236	16.0101	**41.9943**



(a) Hazy image (b) DCP (c) AOD-Net (d) DCPDN (e) GCANet (f) Our method (g) GT

Fig. 5: Comparison of experimental results with state-of-the-art methods

[20] H. Zhao, J. Shi, X. Qi, X. Wang, and J. Jia, "Pyramid scene parsing network." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2016), 2016.

[21] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2015), 2015.

[22] F. Milletari, N. Navab, and S.A. Ahmadi, "V-Net: Fully convolutional neural networks for volumetric medical image segmentation." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2016), 2016.

[23] Ken C. L. Wong, M. Moradi, H. Tang, and T. Syeda-Mahmood, "3D segmentation with exponential logarithmic loss for highly unbalanced object sizes." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2018), 2018..

[24] C.H. Sudre, W. Li, T. Vercauteren, S. Ourselin, and M.J. Cardoso, "Generalised Dice overlap as a deep learning loss function for highly unbalanced segmentations." Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support. 2017.

[25] B. Lim, S. Son, H. Kim, S. Nah, and K.M. Lee, "Enhanced deep residual networks for single image super-resolution." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2017), 2017.

[26] J. Long, E. Shelhamer, and T. Darrell."Fully Convolutional Networks for Semantic Segmentation." In IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2015), 2015.