ABC-NET: AVOIDING BLOCKING EFFECT & COLOR SHIFT NETWORK FOR SINGLE IMAGE DEHAZING VIA RESTRAINING TRANSMISSION BIAS

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ABSTRACT

In recent years, single image dehazing methods based on Atmospheric Scattering Model (ASM) have achieved state-of-the-art results. But the dehazing outputs of those methods suffer from color shift and blocking effect. Our preliminary experiments show that the negative bias of the estimated transmission and the bias of tiny transmission value will cause serious color shift. Therefore, in this study, a new loss function (TransLoss) and a new natural activation function (NAF) are proposed to restrain negative bias of transmission and avoid tiny transmission value from being activated, respectively. Moreover, it is noted that the block effect is caused by patch-level transmission estimation mechanism in existing dehazing models. To address this issue, a new pixel-level transmission estimation module (ETM) is dedicated designed to avoid blocking effect. In the end, an end-to-end CNN dehazing network avoiding color shift and blocking effect is developed, termed as ABC-Net. Experimental results indicate that the ABC-Net outperforms four comparison methods on both synthetic and real-world images.

Index Terms— Single image dehazing, atmospheric scattering model, color shift avoiding, blocking effect avoiding

1. INTRODUCTION

Most single image dehazing methods establish their model by using atmospheric scattering model (ASM) [1] and estimate the parameters of ASM. Transmission is the decisive parameter of ASM, but obtaining it from a single image is an ill-posed problem. Mainstream dehazing methods tend to find prior information or build a deep model to estimate the transmission which could give promising dehazing results. However, the color shift and blocking effect usually can be observed, especially for the serious hazy images (see Fig. 1).

As it is hard to find a prior information that can be suitable all the time, and biases of the estimated parameters solved by deep model are inevitable, so avoiding dehazing distortion is still challenging. In this paper, we explore the correlations between the bias of ASM parameters and the bias of dehazing outputs, and utilize them to restrain dehazing distortion.

We analyze ASM formula and get some interesting discoveries (details are elaborated in section 3.1): 1) Bias of transmission value cause more severe deviation of dehazing output than bias of atmospheric scattering light; 2) Compared with positive bias of transmission, negative bias causes severer deviation of dehazing outputs; 3) In heavy hazy image patch, the transmission value is close to 0. In that case, the bias of transmission has a greater impact on dehazing result and causes color shift more easily. 4) Methods [2, 17] assign a uniform transmission value to one local image patch, which tend to result in blocking effect. While methods without using this strategy could avoid blocking effect, such as [3,4] (see Fig 5).

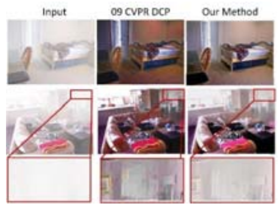

Fig. 1. The dehazing results with different methods. Our method can get clean results without color shift and blocking effect.

Based on the above discoveries, we propose an end-to-end single image dehazing network to address color shift and blocking effect. The network focuses on restricting the negative bias of transmission and the bias of tiny transmission values as well as using pixel-level transmission value assignment approach. Experiments show that our method is capable of restraining color shift and avoiding blocking effect. The major contributions of our work are:

1). We find out the cause of color shift by analyzing the correlation between the bias of ASM parameters and dehazing outputs. Simultaneously, we ascertain the cause of blocking effect by testing different dehazing methods.

2). To avoid color shift, we propose a new loss function, termed as TransLoss, to restrain negative bias of transmission. Concurrently, we design a new activation function, termed as Natural Activation Function (NAF), to restrain tiny transmission value from being activated.

3). To avoid blocking effect, we propose a new pixel-level estimation transmission module (ETM).

4). We design an end-to-end CNN-based dehazing network, termed as ABC-Net, which applies TransLoss, NAF and ETM. The experimental results on both synthetic and real-world hazy databases provide strong support for the effectiveness of our proposed method.

2. BACKGROUND AND RELATED WORK

Atmospheric scattering model (ASM) [1] is suitable for image dehazing, and a common form of it is showed in equations below:

$$I(x) = J(x)t(x) + A\big(1 - t(x)\big) \tag{1}$$

$$t(x) = e^{-\beta d(x)} \tag{2}$$

where *I(x)* is the hazy image. *J(x)* is the haze-free image. β is a coefficient value which represent the degree of haze. *d(x)* denotes the distance from object to camera. *t(x)* is transmission map. For brief expression, we will use *I*, *J*, *t* instead of *I(x)*, *J(x)*, *t(x)* in the rest of this paper. *A* is global atmospheric light factor and it can be considered as a constant among the whole image. A lot of dehazing methods strive to estimate *A* and *t*. If they are obtained, the clean image *J* can be calculated by equation (3):

$$J = \frac{I - A}{t} + A \tag{3}$$

(a) (b)

Fig. 2. (a) The correlation of the bias of estimated global atmospheric light ΔA, the bias of estimated transmission Δt and the bias of dehazing output ΔJ . **(b)** The correlation of the true transmission t_{gt}, the bias of estimated transmission Δt and the bias of dehazing output ΔJ.

Single image dehazing methods are popular recently. These methods can be categorized as: image prior-based methods and deep learning-based methods.

Image prior-based methods try to find prior information that can be definitive in improving visibility of hazy images. DCP [2] (2009) estimates the transmission map *t* based on dark channel prior and get haze-free image by equation (3). Berman [5] (2016) solves the dehazing problem by a non-local prior named as haze-line.

Deep learning-based methods try to estimate parameters of ASM by neural networks. DehazeNet [3] (2016) use CNN [14] to obtain multi-scale features and output transmission. AOD-Net [4] (2017) and IASM-Net [6] (2018) are end-to-end neural networks based on re-formulated ASM which can output haze-free image directly.

However, both deep learning-based methods and image prior-based methods cannot avoid bias in estimating ASM parameters, and these uncertain biases will cause color shift and blocking effect.

3. PROPOSED METHOD

3.1. Analysis of the causes of color shift & blocking effect

Color shift and blocking effect reflect the distortion of dehazing result. In order to analyze the correlation between bias of dehazing output and bias of ASM parameters, we denote that:

$$A_{est} = A_{gt} + \Delta A \tag{4}$$

$$t_{est} = t_{gt} + \Delta t \tag{5}$$

$$J_{est} = J_{gt} + \Delta J \tag{6}$$

where A_{gt}, t_{gt}, J_{gt} denote true atmospheric scattering light, true transmission, ground truth haze-free image, respectively. A_{est}, t_{est}, J_{est} are the corresponding estimated values. ΔA, Δt, ΔJ are the bias of each parameter. From equation (3)(4)(5)(6) we can obtain:

$$\Delta \mathrm{J} = J_{est} - J_{gt} = \frac{\Delta A t_{gt}\left(t_{gt} + \Delta t - 1\right) + \Delta t\left(A_{gt} - I\right)}{t_{gt}\left(t_{gt} + \Delta t\right)} \tag{7}$$

To better understand equation (7), we assign $\Delta t = 0$, $A_{gt} = 1.0$, $t_{gt} = 0.6$, $I = 0.8$ to plot the correlation figure of ΔA , Δt and ΔJ (see Fig. 2 (a)). Similarly, we assign $\Delta A = 0$, $A_{gt} = 1.0$, $I = 0.8$, to plot the correlation figure of t_{gt}, Δt and ΔJ (see Fig. 2 (b)).

Color shift issue. It is caused by the bias of dehazing output. From equation (7) and Fig. 2 (a) and (b), we can find out that: 1) Compared with the bias of atmospheric scattering light ΔA, the bias of transmission Δt cause more severe distortion of dehazing output; 2) Compared with positive bias of transmission, negative bias causes severer distortion of dehazing output; 3) When transmission has tiny value (heavy hazy condition), the bias of transmission will have a great impact on dehazing output.

Blocking effect issue. We discover that the results of methods like [2,3], that have patch-level processing mechanism are more likely to have blocking effect. Patch-level processing mechanism means assigning a uniform transmission value to an image patch. Methods like AOD-Net [4] can avoid blocking effect with another processing mechanism that assign an estimated transmission to each pixel (see Fig. 5). What's more, blocking effect of dehazing outputs is more obvious in heavy hazy condition (see Fig. 5 (b)). Based on these observations, we conclude that the blocking effect is mainly caused by the patch-level transmission processing mechanism. And the bias of transmission will make the blocking effect more obvious.

Hence, to avoid color shift and blocking effect, we can restrain the bias of transmission and use a pixel-level transmission processing mechanism.

3.2. TransLoss

Some methods use MSE loss function to learn transmission map, such as DehazeNet [3], which only consider bias between t_{gt} and t_{est}. But transmission is only an intermediate variable, the ultimate goal is to make dehazed image J_{est} consistent with the ground truth haze-free image J_{gt}. So, we mainly consider the bias of dehazing output in our transmission training loss function, termed as TransLoss. Based on this idea, we denote $Loss_t = \Delta J$, where $Loss_t$ is the loss function of training estimating transmission module. From equation (3)(6), we can get:

$$Loss_t = \Delta J = J_{est} - J_{gt} = (I - A)\left(\frac{1}{t_{est}} - \frac{1}{t_{gt}}\right) \tag{8}$$

Because $(I - A)$ is irrelevant to transmission t as well as always positive, we omit it and get a simplified loss function:

$$Loss_t(t_{est}, t_{gt}) = \frac{1}{N}\sum_{x=1}^{N}\left|\frac{1}{t_{est}(x)} - \frac{1}{t_{gt}(x)}\right| \tag{9}$$

where x is pixel index, N represents image size, the absolute value is taken to ensure TransLoss has a minimum value. For better understanding, we plot this loss function in Fig. 4 (a). We can find out from equation (9) and Fig. 4 (a) that TransLoss reaches down to the minimum when the value of t_{est} is equal to the value of t_{gt}. At the same time, in order to restrain negative bias, TransLoss can give a greater penalty to the negative bias than the positive one.

3.3. Natural activation function (NAF)

Existing activation functions are not perfectly suitable for estimating transmission. As transmission value is in the range of [0, 1], but ReLU [7] tend to output values bigger than 1. Sigmoid can confine the output range to [0,1], but it gives a negative estimated value a positive output, which make it unsuitable, too. BReLU [8] can also confine the output range to [0,1]. But it saturates too fast and kills the gradients. The appropriate activation function should have such features: 1) Its output range should be [0,1]. 2) It should limit negative and tiny positive value to be activated to avoid destructive dehazing output bias in heavy hazy condition; 3) It should maintain a reasonable activation range and gradient to facilitate training. Inspired by a natural activation function model, the Leaky Integrate-and-Fire (or LIF) [9], we design a similar activation function. Refer to equation (2), we choose e^{-3} as an appropriate threshold to achieve a balance between dehazing ability and restraining transmission bias ability. Values less than e^{-3} will be assigned as e^{-3}. It won't impair the dehazing ability within 30 meters depth in light hazy condition ($\beta = 0.1$), while 6 meters depth in heavy hazy condition ($\beta = 0.5$). Hence, we design a novel activation function and name it as Natural Activation Function (NAF).

$$NAF(x) = \begin{cases} e^{\frac{-3\times e^{-3}}{x}} & , x > e^{-3} \\ e^{-3} & , x \leq e^{-3} \end{cases} \tag{10}$$

We plot NAF in Fig. 4 (b). The NAF have all the three features we list above and make dehazing output more natural by restraining

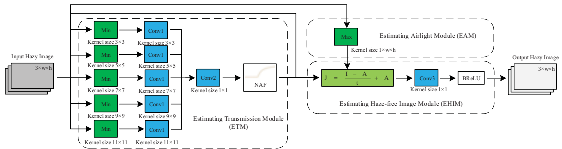

Fig. 3. The network architecture of our ABC-Net.

the bias of transmission.

3.4. Estimating Transmission Module (ETM)

In DCP [2], the transmission map is obtained by:

$$t = 1 - \min_{c}\left(\min_{\Omega}\left(\frac{I}{A}\right)\right) \tag{11}$$

where c denote the color channels and Ω denote the local patch of hazy image I. Multi-scale feature has been proven to be effective for dehazing in [10]. This technique is also used in DehazeNet [3] and shows good performance. Following those work, we use a min pooling layer to get dark channel feature, and then use two convolutional layers to convert the feature into transmission. Multi-scale mechanism is exploited in both pooling layer and convolutional layers. The ETM does not use downsampling, so it can estimate a transmission value for each pixel in the input image. To avoid the bias of transmission estimate, we use NAF as the activation function of ETM. The ETM works as follows:

$$F_1^n = \min_{c}\left(\min_{\Omega}(I)\right), where\ n \in \{1,2,3,4,5\} \tag{12}$$

$$F_1^6 = concat\{F_1^1, F_1^2, F_1^3, F_1^4, F_1^5\} \tag{13}$$

$$F_2^n = W_2^n F_1^6 + B_2^n, where\ n \in \{1,2,3,4\} \tag{14}$$

$$F_2^6 = concat\{F_2^1, F_2^2, F_2^3, F_2^4\} \tag{15}$$

$$F_3^1 = W_3^1 F_2^5 + B_3^1 \tag{16}$$

$$F_3^2 = NAF(F_3^1) \tag{17}$$

where Ω^n denote different patch size, which is one of $\{3\times3, 5\times5, 7\times7, 9\times9, 11\times11\}$. And $concat$ means concatenating the inputs.

3.5. ABC-Net

Following AOD-Net [4] and IASM-Net [6], we design an end-to-end dehazing network using ASM. For avoiding color shift, we apply TransLoss and NAF to our dehazing network. For avoiding blocking effect, we use pixel-level transmission processing mechanism. We name our network as ABC-Net as it has ability to Avoiding Blocking effect & Color shift. The network architecture of ABC-Net is shown on Fig. 3. This network has three modules: 1) estimating transmission module (ETM); 2) estimating atmospheric scattering light module (EAM); 3) estimating haze-free image module (EHIM). The detail of ABC-Net is described in below.

Estimate transmission map details are described in section 3.4.

Estimate atmospheric scattering light: In equation (3), the global atmospheric light A usually can be considered as a constant due to its homogeneousness. So, we use a max pooling layer to get the maximum value from each channel of the input hazy image. The EAM works as follows:

$$A^c = max(I^c), where\ c \in \{r, g, b\} \tag{18}$$

$$A = concat\ (A^r, A^g, A^b) \tag{19}$$

Estimate haze-free image: After obtaining transmission t and global atmosphere light A, the equation (3) is employed to figure out the haze-free image J. In order to refine the output and remove noise, we process J with a convolutional layer followed by a BReLU activation function. The EHIM works as follows:

$$F_4^1 = \frac{I - A}{F_3^2} + \mathrm{A} \tag{20}$$

$$F_4^2 = W_4^1 F_4^1 + B_4^1 \tag{21}$$

$$F_4^3 = \mathrm{BReLU}(F_4^2) \tag{22}$$

Our proposed ABC-Net is delicately designed for dehazing with restraining bias and avoiding color shift and blocking effect.

4. EVALUATIONS

4.1. Datasets and training details

Adequate training data is essential for CNN-based methods, but since it is very difficult to collect both clean and hazy images of a same scene, real world dehazing databases are very scarce. Lots of methods, such as DehazeNet [3], AOD-Net [4], use ASM [1] to synthesize dehazing dataset. By convention, we use NYU-Depth-v2 [11] to synthesize our dataset. NYU-Depth-v2 provide 1449 clean images and theirs corresponding depth information. Referring to equation (1)(2) and setting $\beta = 0.35$ (light hazy condition), we use 1000 images and the rest 449 images to create training and testing set, respectively. In order to verify the robustness and generalization of our method, we use the rest 449 images to make another testing set by giving $\beta = 0.75$ (heavy hazy condition).

In training session, we use TransLoss to train the estimating transmission module (ETM), under the supervision of ground truth transmission maps. Then, we use MSE loss to training the whole ABC-Net, under the supervision of ground truth haze-free images. The former is introduced in equation (9) and the latter can be found in equation (23). With the help of stochastic gradient descent algorithm, we take 100 iterations to train ETM, and take another 100 iterations to train the whole network, then repeat the cycle until both ETM and ABC-Net converge. While in testing session, hazy images are input into the model and clean images are used for evaluation.

$$Loss_J(J_{est}, J_{gt}) = \frac{1}{N}\sum_{x=1}^{N}\left(\frac{1}{J_{est}(x)} - \frac{1}{J_{gt}(x)}\right)^2 \tag{23}$$

4.2. Evaluation of restraining bias capability of ABC-Net

In order to evaluate the restraining capability of ABC-Net to negative bias of transmission, we collect the output transmission of ETM of all the 449 testing samples with $\beta = 0.35$. Comparing with their ground truth transmission image, we calculate the bias of each pixel on each sample pair to get an average bias. The average bias of 449 testing samples is a tiny value, 0.0586. And all values of the biases are small and within $[-0.13, 0.28]$. At the same time, most of them (335 of 449, 74.6%) have positive bias of transmission. It shows that our ABC-Net can restrain negative bias of transmission effectively.

In order to test the restraining capability of ABC-Net for tiny transmission value, we also use the above testing set with $\beta = 0.35$ to evaluate. Among 449 testing samples, none of them have transmission value lower than e^{-3}. It shows that our ABC-Net can restrain tiny transmission value effectively.

4.3. Evaluations on synthetic hazy image dataset

We evaluate ABC-Net on two different synthetic hazy datasets, which are obtained by setting $\beta = 0.35$ and 0.75, respectively. Note that we only train our model on $\beta = 0.35$ training dataset. Dataset with $\beta = 0.75$ is created only for verifying the robustness and generalization of ABC-Net. Another four high-performance methods [2-5] are reimplemented for comparing. The comparing results are shown in Fig. 5 and Table 1.

With $\beta = 0.35$ (see Fig. 5 (a)), the results of image prior-based methods suffer from color shift in heavy hazy area or white image patches, and two deep learning-based methods, DehazeNet [3], AOD-Net [4] avoid color shift but produce poor-effect dehazing

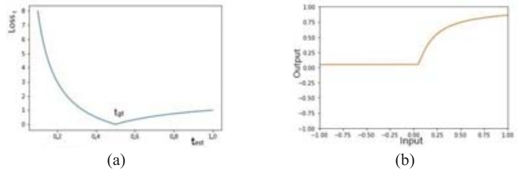

Fig. 4. (a) The plot of our proposed loss function, TransLoss. The loss reaches down to the minimum when the estimated transmission value t_{est} equal to t_{gt}. **(b)** The plot of our proposed activation function, Natural Activation Function (NAF).

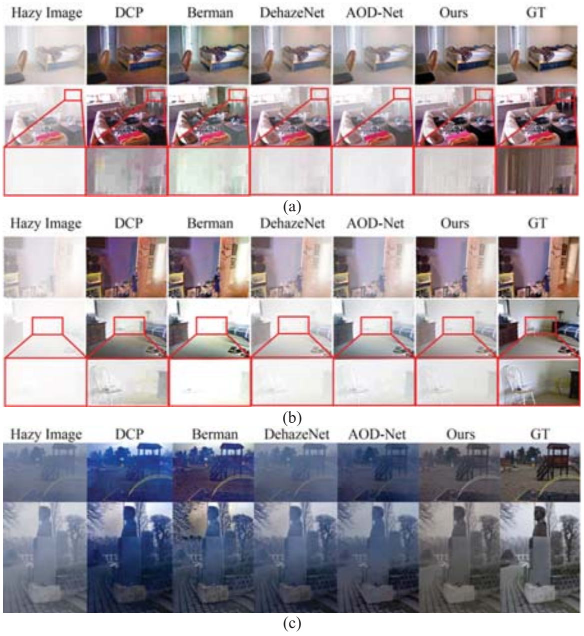

Fig. 5. (a) Evaluation on synthetic hazy dataset with $\beta = 0.35$. Results demonstrate that our method can get clean dehazing results with avoiding color shift and blocking effects. While others get unclean dehazing results, or suffer from blocking effect and color shift. **(b)** Evaluation on synthetic hazy dataset with $\beta = 0.75$. **(c)** Evaluation on real-world hazy dataset.

outputs. If zoom in for details, it can be found that all the comparing methods have blocking effect in various degrees, while the results of our ABC-Net are haze-free as well as avoiding color shift and blocking effect. It shows our method has the most outstanding performance in enhancing visibility of all the compared methods.

Evaluating on datasets with $\beta = 0.75$ (heavy hazy condition), it shows all comparing methods' dehazing results and ours in Fig. 5 (b). The comparing methods either retain heavy haze in output image, or contain obvious color shift. And none of them avoid blocking effect (zoom in if interest in details). However, our ABC-Net still performs well, maintaining a fine dehazing capability as well as avoiding color shift and blocking effect, even though it is only trained under light hazy condition ($\beta = 0.35$) but tested in heavy hazy condition. It shows our ABC-Net not only performs the best at balancing between maintaining dehazing capacity and restraining severe bias, but also has great robustness and generalization.

Although our work focuses on improving visibility, it also does well in quantitative comparisons. Peak Signal to Noise Ratio (PSNR)

Table 1. Quantitative comparisons for different methods. Our method ranks all first of those 3 indexes on the whole 3 datasets

Database	Index	DCP	Berman	Dehaze Net	AOD-Net	Ours
Synthetic β = 0.35	PSNR	17.32	16.57	14.65	12.77	**17.78**
	SSIM	0.785	0.763	0.749	0.688	**0.785**
	CIEDE 2000	10.886	13.066	14.205	18.491	**9.605**
Synthetic β = 0.75	PSNR	13.52	10.30	7.84	8.53	**13.90**
	SSIM	0.654	0.613	0.546	0.539	**0.660**
	CIEDE 2000	16.560	24.665	32.386	30.260	**16.461**
Real-world O-Haze	PSNR	16.59	16.61	16.21	17.13	**19.02**
	SSIM	0.735	0.750	0.666	0.664	**0.752**
	CIEDE 2000	20.745	17.088	17.348	15.774	**10.144**

[15] and Structural Similarity Index Measure (SSIM) [16] are commonly used in evaluating dehazing results. CIEDE2000 [12] measures accurately the color difference between two images and generates values in the range $[0,100]$, with smaller values indicating better color shift avoiding ability, which can evaluate the level of color restoration. We calculate PSNR, SSIM, CIEDE2000 of all comparing methods and our method and provide the result in Table 1. Our ABC-Net ranks all first in PSNR, SSIM and CIEDE2000 on datasets with $\beta = 0.35$ and 0.75, even it is only trained on dataset with $\beta = 0.35$. It implies that our bias restrain strategy is successful.

4.4. Evaluations on real-world hazy image dataset

We evaluate our method and four comparing methods on real-world hazy image dataset O-Haze [13]. It has 45 images, we choose 40 of them to train our model from scratch and 5 images are used as testing samples. We present some of the results in Fig. 5 (c). In addition, to compare with more deep learning-based method, we retrain AOD-Net [4] and show results in Fig. 5 (c), too.

In Fig. 5 (c), we can see that our results not only are the closest to the ground truth, but also performs best in avoiding color shift and blocking effect. After dehazing, the results of the compared methods are blue, while ours restore the color. What's more, in Table 1, our method performs the best in PSNR, SSIM and CIEDE2000 on O-Haze dataset. Therefore, the qualitative and quantitative results show that our method leads to a superior performance in real world hazy condition.

5. CONCLUSIONS

In this paper, we analyze the causes of color shift and blocking effect of image dehazing algorithms, and find that positive and negative bias of transmission have different effects on dehazing results. Based on these discoveries, we propose a new TransLoss, a new natural activation function (NAF) and a new transmission estimating module (ETM), respectively. We further incorporate the proposed TransLoss, NAF and ETM to form a unified dehazing network called ABC-Net, which can restrain the bias of transmission and calculate pixel-level transmission value. Experimental results show our method can get outstanding clean dehazing outputs without blocking effect and color shift.

6. ACKNOWLEDGMENTS

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