A Framework For Single Image Dehazing Using DWT Based Cross Bilateral Filter Fusion of Generative and ASM Models

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Abstract—Due to the latest advancements in technologies like artificial intelligence, machine learning, and deep learning in image processing, computer vision, and their uses in various applications, there has been a lot of interest in the restoration of murky images. This paper gives a novel single-image dehazing (SID) framework for the restoration of single hazy image (SHI). The framework has three parts. The first part of the framework comprises three networks. A white-balanced auto-encoder network in the front, followed by a pair of sequential auto-encoder networks at the end for image dehazing (ID). A white balance auto-encoder network is used for correcting the white balance error in the input hazy image (HI). Pair of sequential autoencoder networks gives haze-reduced output by taking corrected white balanced error image as input. The second part comprises an ASM-based model Dark Channel Prior (DCP) for ID. DCP produce haze-free images (HFI) by taking HI as input. The third part presents the fusion model for integrating the first and second parts of the framework. DWT-based cross bilateral filter model is the fusion model (FM) to get the final HFI. The first part of the framework is trained by using a hybrid loss function (perceptual loss function combined with MSE loss function) on OHAZE, I-HAZE, and MRFID data sets. The proposed framework got considerably good result in terms of Structural Similarity Index (SSIM), Peak signal-to-noise ratio (PSNR), compared with cutting-edge methods.

Index Terms—Auto-encoder, Residual learning, rectified linear activation unit (ReLU).

I. Introduction

Haze is an atmospheric phenomenon with a wide variety of sources and obscures the clarity of the sky by creating a milky appearance in the air. It causes very low visibility, and makes it difficult to see in hazy conditions. The image captured in hazy conditions suffer from the haze in the environment which leads to low light, colour distraction and thus a blurry appearence.

Recovery of the original image from HI is essential for many image processing applications because of the requirement of clear images for most of the applications, such as object recognition, image classification, object detection, surveillance, etc. The formulation of HI based on the physical model of atmosphere is developed by Narasimhan et al. [1] called as atmospheric scattering model (ASM) as given in eq. (1).

$$H(x) = C(x)\Upsilon(x) + A(1-(\Upsilon(x)) \quad (1)$$

$$\Upsilon(x) = e^{-\gamma d(x)} \quad (2)$$

where, $H(x)$ is the HI, $C(x)$ is the image without haze components, $\Upsilon(x)$ is the transmission map, γ is the coefficient value to represent haze, $d(x)$ is the distance from object to camera and A is the global atmospheric light factor. Dehazing methods try to find the unknown factors Υ and A to find the C. Which can be further defined as in eq. (3).

$$C(x) = \frac{H(x) - A}{\Upsilon(x)} + A \quad (3)$$

In the above eq. (3), A is the atmospheric light factor and it can be assumed as a constant through the entire image, but in reality, the atmospheric light is not constant; rather, it varies from pixel to pixel, and makes the image non-homogeneous. The changed version of ASM [2] is a non-homogeneous ASM (NHASM) given by eq. (4).

$$H(m,n) = C(m,n)\Upsilon(m,n) + A(m,n)(1-(\Upsilon(m,n)) \quad (4)$$

where m,n is the index of the image matrices H, C, Υ and A following is the modified recovery equation is given below in eq. (5).

$$C(m,n) = \frac{H(m,n) - A(m,n)}{\Upsilon(m,n)} + A(m,n) \quad (5)$$

Although, considering the atmospheric light as nonhomogeneous, the

NHASM has drawbacks of not estimating atmospherice light and transmission map correctly for a given image. The advancement of generative models (GM) made direct mapping of haze and haze-free images possible. One of the GM [3] is auto-encoders, which has an encoder-decoder pair for image mapping defined as

$$C^{?} = g_{\Theta}(f_{\theta}(H)) \tag{6}$$

$$C \approx C^{?} \tag{7}$$

where H, is the HI, C is the clear image, $f_{\theta}(x)$ is encoder, $g_{\Theta}(x)$ is decoder and $C^{?}$ is the restored image.

The GM give a possibility to explore ID without the use of ASM. Although, GM use large data sets and lots of computation power to obtain results, but give good results. So, we further investigate both models by combining them using image fusion methods. By doing this, we integrate performances of both ASM and GM for SID. The proposed novel framework combines both ASM and GM using a discrete wavelet transform (DWT)-based cross bilateral filter image fusion method for SID.

The remainder of this paper is structured as follows in Section II, which examines related work. Section III provides an explanation of the suggested framework, while Section IV presents the experiments' findings. In Section V, the conclusions are reached.

II. Related Work

Various methods were proposed for ID in computer vision applications. Most of the methods fall into two major categories: prior-based (PB) approaches and learning-based (LB) approaches. The PB methods depend on the ASM, while the LB methods do not. ID methods were further divided into ASM-based models and NHASM.

Generally, PB models use, He et al. [4] proposed DCP method based on the fact that a C has a pixel in RGB colour channels close to zero (minimum) intensity. Zhu et al. [5] proposed Color Attenuation Prior (CAP) based on the observation that, as the fog density grows, so does the disparity between pixel intensity and saturation. Sun et al. [6] presented Bright Channel Prior (BCP) method is based on assumption that clear images has a pixel in RGB colour channels which has maximum intensity.

Berman et al. [7] given an algorithm based on a nonlocal prior called haze-lines with linear complexity. In PB models and among several other methods, DCP gained more popularity.

All these PB methods are used to estimate the variables of ASM equation and recovery of the HFI using ASM. Most of the PB models assume global atmospheric light as a constant or calculate atmospheric ambient light values using DCP and take top one percent of the pixel points atmospheric ambient light values as a atmospheric light.

LB approaches try to estimate parameters of ASM by neural networks and some approaches directly map HI to HFI like generative adversarial networks (GANs), auto-encoder, etc. Cai et al. [8] proposed DehazeNet which use Convolutional Neural Network (CNN) with Bilateral Rectified Linear Unit (BReLU) activation function for ID.

Li et al. [9] proposed All-in-one dehazing network (AODNet) an end-to-end neural network that produces HFI directly. Tran et al. [10] proposed a novel encoder-decoder network with a guided transmission map for SID (EDN-GTM). EDNGTM designed using the U-Net framework with the swish activation function in its CNN layers. The HI and its transmission map were given as input to the EDN-GTM to produce a HFI. Liu et al. [3] proposed a GMAN using a residual learning network for ID. Ren et al. [11] given the EDN and fusion strategy for ID.

However, bias in predicting ASM parameters cannot be avoided by either deep learning-based approaches or image PB methods, and these uncertain biases result in color shift and blocking effects.

GANs and Front White Balance Network (FWB) are used for color shift free ID. Engin et al. [12] proposed CycleGAN based on Cycle-Consistency with perceptual loss (VGG loss). Sun et al. [13] added iterative mode to CycleGAN network and form ICycleGAN model for ID. Based on their concept, so many versions of GANs have been developed for ID.

Based on the non-homogeneous atmospheric light estimation of hazy images, the NHASM was designed. Wang et al. [14] proposed fully NHASM with CNN which estimate three parameter maps: angular scattering coefficient (ASC), depth and atmospheric light factor (ALF) with loss functions for ASC and depth estimating module, termed as β-Loss and D-Loss respectively.

Wang et al. [15] proposed Front White Balance Network (FWB) Network for color shift correction using nonhomogeneous atmospheric light model which used White Balance Network (WBN) in front of network called FWB and estimates atmospheric light with FWB loss function and estimate transmission map using CNN based model for recovery of HFI using ASM recovery eq. (3).

Fusion-based methods give good result for ID but has high complexity when compared with other methods. Ancuti et al. [16] proposed to fuse two images of corrected white balance error and contrast-enhanced images. Wang et al. [17] given a multi-scale fusion and Laplacian-Markov random field for depth map estimation in HI, and edge preserved fusion which gives depth map and sharp defog image form HI.

Now a days research is going on in the direction of feature fusion [18].

III. Proposed Framework

The proposed framework is a combination of ASM and Non-ASM models. The IH (input) is given to ASM model and non-ASM model to generate HFI. The two HFI are fused using DWT based cross-bilateral filter image fusion method [22], [27] . Non-ASM model is designed using auto-encoder networks in which the input travels through three EDN, first the input is passed through WBN which is explained in

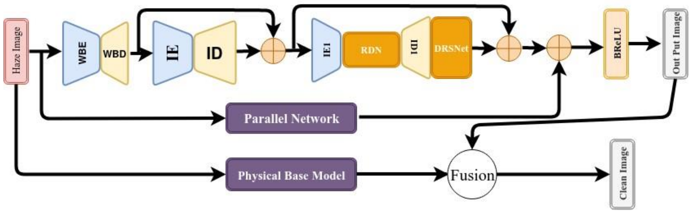

Fig. 1. Overview of proposed Framework consisting of three stages. 'WBE' and 'WBD' form the encoder-decoder pair (EDP) for deep white balance network, 'IE' and 'ID' form the EDP for image dehazing, 'IE1' and 'ID1' form the EDP with 'RDN' for ID. 'RDN' denotes residual dense block, 'DRSNet' is the Detail Reconstruction Sub-network, $\oplus$ denotes element-wise summation

subsection III-A, to correct white balance error. The corrected white balanced image is sent to the auto- encoder as in subsection III-B and then it is passed to Generic Auto-encoder Network (AEN) with detail reconstruction sub-network at the end as explained in subsection III-C.

The parallel network (PN), as in subsection III-E is used to enhance the details of haze image. The output image of PN is combined with output of Generic AEN to get detail haze-free image (DHFI) and the DHFI is passed through the BReLU layer to get output HFI. ASM model uses DCP subsection III-F to recover HFI form HI. The recover HI image and output HFI are fused by using DWT-based cross-bilateral filter image fusion method as explained in subsection III-G.

Only the non-ASM models subsections (III-A,III-B,III-C,III-E) networks are trained with datasets of haze image and its corresponding haze-free image. where physical model and fusion framework are not trained.

A. White Balance Network (WBN)

SID is a method of taking an single haze image (SHI) as input, process it and gives an HFI as close to original image as possible. Generally, methods are proposed for SID with traditional white balance technology, which correct the white balance error after dehazing. Inspired by [14], [15] our frame work uses white balance network which will correct color shift before generating dehazing results. WBN has a encoder (WBE) and a decoder (WBD) with bottleneck in between WBE and WBD. The WBN is design of U-Net [19] with skipconnections between WBE and WBD.

WBE has four-levels with increasing number of filters of factor 2 starting with 24 filters and ends with 192 filters.

Each level of WBE consist of five layers. First four layers are a pair of CNN layers followed by ReLU activation layer i.e (CNN + ReLU layer). Second CNN layer which is third layer of five layers has skip-connection to WBD corresponding level. The fivth layer is max-pooling layer for down-sampling.

WBE's level is given by equation (9) bottleneck has four layers which is a pair of CNN followed by ReLU activation.

$$y = \delta(X \circ f) \tag{8}$$

$$y_i^1(X) = MP(\delta^1(y(\delta^1(y)))) \tag{9}$$

where X is the input to CNN, $\circ$ convolution operation, f is the filters of CNN, is CNN, δ is the ReLU activation function (AF), δ^1 is the ReLU AF layer, MP is the max-pooling, y_i^1 level of WBE.

White Balanced Decoder has four levels with decreasing number of filters of factor 2. At each level it has three parts. First part has Transpose-CNN which is used to up-sampled the input followed by ReLU activation layer. Second part has concatenation layers with axis 3 which will concatenate with encoder corresponding levels with skip-connection. Finally pair of CNN followed by ReLU activation layer except the fourth level has an additional 1×1 CNN layer with 3 filters which gives a output image with corrected white balanced error. The corrected white balanced image is send to EncoderDecoder network subsection III-B as an input.

$$g = \delta(y \circ f) \tag{10}$$

$$g^1 = Cat(y,g) \tag{11}$$

$$g_i^1 = (g(\delta(g^1 \circ f)) \tag{12}$$

where, g is CNN layer, $Cat(.)$ is concatenation operation, g^1 is skip-connection, g_i^1 represent single level in WBD.

B. Encoder-Decoder for Image Dehazing (IE-ID)

The image dehazing auto-encoder [20] is a pair of encoder and decoder network which gives haze-free image after taking an hazy image as input. First the given input (high-dimensional data) is passed throughout encoder which translate the input images into lower-dimensional latent code as in eq. (13).

$$Z = f_\theta(x) \tag{13}$$

where Z is the encoder in auto-encoder. The decoder network takes lower-dimensional latent code as input and gives a reconstructed output as close as the original HFI. The total EDN is given as in eq. (6).

ID encoder has 3 levels. In each level, it has one CNN layer followed by average pooling layers, which is used to downsampled the given corrected white balanced image as input. The bottleneck network has 2 completely connected Dense layers with 10 neurons each. Image dehazing decoder has 4 levels, in first 3 levels its has one CNN layer followed by up-sampling layer, all the CNN layers have same numbers of filters ie. 64 in both encoder and decoder network except in the fourth level of Decoder which has 3 filters for creation of RBG a corrected white-balanced-hazed-reduced image as output.

C. Generic Auto-encoder Network with Detail Reconstruction Sub-network

This model is inspired by [3]. Which is completely generic, with no consideration of image dehazing in its design. The model has an encoder, residual dense block and decoder. The encoder have 4 CNN layers, the first two layers have 64 filters and the remaining two CNN with 128 filters. Followed by a two blocks as 3 CNN layers followed by an addition layer with ReLU activation layers and the second two blocks have 5 CNN layers followed by an summation layer with ReLU activation layer. One of the first two layers of RDB is defined as in equation (14)

$$RDB = \delta((((X \circ f_1) \circ f_2) \circ f_3) + X) \quad (14)$$

where $f_1 = f_2 = f_3 = 64$. The decoder layer has an RDB residual dense block (RDB), RDB comprises 4 blocks. First of 4 layers with pair transpose CNN layers on top and two CNN layers followed by an element-wise summation layer with ReLU activation function to generate a HFI as output.

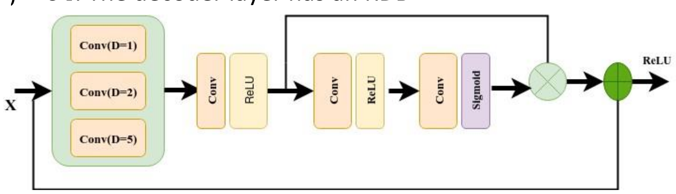

Fig. 2. Enhanced Pixel-Wise Residual Attention Block (ERPAB), ⊗ denotes element-wise multiplication

D. Detail Reconstruction Sub-network (DRSNet)

Detail Reconstruction Sub-network (DRSNet) [21] is subnetwork contains of series of enhanced pixel-wise residual attention block (ERPAB) as shown in Fig. 2. ERPAB has a parallel dilated residual block (PDRB) and a pixel-wise attention block (PAB).

PDRB contains three dilated CNN layers with the dilated factor of d = 1,2,5. The three dilated CNN layers are concatenated into one layer and passed to the CNN layer with sigmoid AF. PDRB is defined as in eq. (15).

$$PDRB = \sigma(Z_2(Cat\begin{pmatrix} Z_{11,1}(X) \\ Z_{12,2}(X) \\ Z_{13,5}(X) \end{pmatrix})) \quad (15)$$

where $Z_{i,j,d}$ denotes the weight of dilated convolution of dilation factor of d at i^{th} column and j^{th} row, $Cat(.)$ is a concatenation operation, Z_i denotes CNN. Pixel-wise Attention Block (PAB) is designed to enhance pixel-wise correlation by taking PDRB as input as given in eq. (16).

$$PAB(PDRB) = Z_2(\sigma(Z_1(PDRB))).PDRB \quad (16)$$

Form equation (15) and (16) the ERPAB is defined as in equation (17)

$$ERAB = \sigma(PAB(PDRB) + X) \quad (17)$$

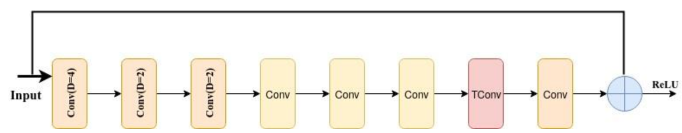

Fig. 3. Parallel-Network

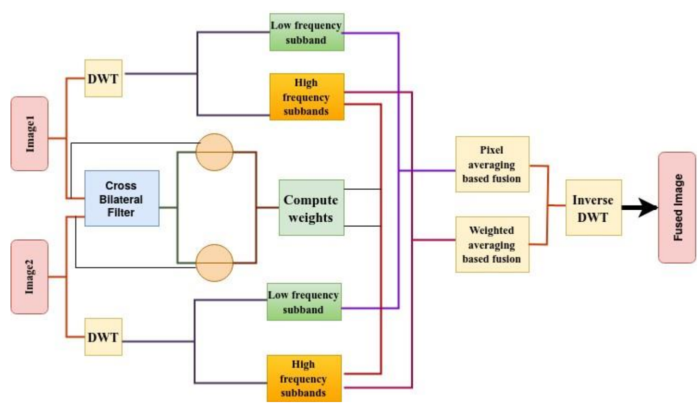

Fig. 4. Fusion Framework: DWT and Cross Bilateral Filter based Image fusion

E. Parallel-Network (PN)

A parallel network (PN) is the network to enhance the content of the input image, as shown in Fig. 3. The PN comprises 8 layers in which first three are CNN layers with the dilated factor 4, 2, and 2 in series. Followed by three CNN layers with the dilated factor 1. Next the transpose CNN layer is used for up-sampling. Lastly a CNN layer followed by element-wise summation layer with input image and ReLU activation layer at the end. As in the eight layer PN takes HI as input and gives a detail enhanced HI as output. The output images is passed through BReLU and combined to the output of DRSNet followed by BReLU to get output image as shown in Fig. 1.

F. Atmospheric Scattering Model (ASM)

The formulation of HI based on the physical model of the atmosphere is developed by [1] called as ASM formulated as eq. (1). The ASM model first estimate the dark channel map (DCM) using DCP, the top 0.1 percent brightest pixels of DCM with a corresponding pixel value in an input image taken as atmospheric light A. Transmission map is generated by using A and local patch size. The transmission map is refined by using Guided-filter. Then with the help of equation
(3) the HFI is recovered.

G. Fusion-Framework

The proposed fusion framework is shown in Fig. 4.

- In the proposed fusion method, two images X and Y are passed over a DWT transform to decompose the images into low (LL) and high-frequency sub-bands LH,HL, and HH.
- Apply pixel averaging method on low-frequency subbands to fuse and obtain the average fused coefficient (LL_{new}).
- Combine high-frequency sub-bands by their weighted average of both transformed images. Weights are computed by subtracting input images (X and Y) from CrossBilateral Filter output image to get weights of X and Y as (Wt_X) and (Wt_Y).
- Fuse the high-frequency sub-bands with their respective weights using equation (18)

$$HL_{new} = \frac{Wt_X * HL_X + Wt_Y * HL_Y}{Wt_X + Wt_Y} \tag{18}$$

  Similarly obtain fused wavelet coefficients LH_{new} and HH_{new}.
- Perform inverse DWT over the fused coefficients $LL_{new},LH_{new},HL_{new}$ and HH_{new} for the reconstruction of the fused image and apply contrast limited adaptive histogram eualization over the fused image to control over-amplification of contrast of fused image.

H. Loss Function

The proposed framework, combined two loss functions to form a hybrid loss function (HLF). MSE and VGG loss combined to form a HLF to train the network. VGG loss measures the global discrepancy between the features of generated image and the original image. These features are extracted from a well-trained CNN based model called VGG19. The VGG-19 model is pre-trained on Image-Net data-set for feature extraction. The VGG loss function is expressed as in eq. (19):

$$L_P(GI,OI) = L_{MSE}(VGG(GI),VGG(OI)) \tag{19}$$

where, L_{MSE} is MSE loss function, GI is a generated image (final output) and OI is the original image (ground truth). The hybrid loss function is expressed as in eq. (20)

$$L_{Hy}(GI,OI) = L_{MSE} * 0.5(L_P(GI,OI)) \tag{20}$$

IV. Experiments and Results

A. Data-sets and Data Preparation

Three benchmark data sets, I-HAZE [10], O-HAZE [12], and multiple real-world foggy image dataset (MRFID) [26] are used for experiments on dehazing tasks. By taking I-HAZE data-set with 35 indoor HI with ground truth haze-free images (GTHFI). O-HAZE data-set with 45 outdoor HI with GTHFI. The MRFID data-set has 200 GTHFI with 800 haze images in which one ground truth image has 4 haze images with four different haze densities. proposed framework takes a total of 280 ground truth images and 880 haze images for experiments. The data sets are divided into training and testing sets for training and testing the proposed framework.

TABLE I
Performance comparison on I-HAZE and O-HAZE

Method	I-HAZE		O-HAZE	
	PSNR	SSIM	PSNR	SSIM
DCP	14.43	0.751	16.78	0.653
CAP	12.24	0.665	16.08	0.596
DehazeNet	27.93	0.606	28.03	0.493
RBDC	27.69	0.327	27.58	0.548
GMAN	27.72	0.223	27.97	0.138
OURS	27.54	0.360	27.91	0.504

TABLE II
Performance comparison on multiple real-world foggy image dataset (MRFID)

Method	MRFID-I		MRFID-II		MRFID-III		MRFID-IV	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
DCP	27.98	0.484	27.84	0.316	27.86	0.273	27.88	0.225
CAP	27.76	0.299	27.82	0.171	27.85	0.147	27.84	0.15
DehazeNet	27.87	0.133	27.86	0.027	27.86	0.066	27.83	0.009
RBDC	27.85	0.180	27.86	0.070	27.86	0.022	27.84	0.031
GMAN	27.96	0.213	27.90	0.140	27.90	0.102	27.88	0.047
OURS	27.95	0.246	27.98	0.236	27.94	0.238	27.95	0.165

B. Experimental Setting

The experiments were performed on Google Co-lab pro. The Framework takes input size of 224 × 224. The number of training epochs is 70 with Adam optimizer of learning rate

0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$ with batch size of 10. The dehazing performances is measured by using PSNR and SSIM metrics.

C. Results

The performance of the Framework on I-HAZE, O-HAZE, and MRFID data sets is compared with those of other approaches in Table-I and Table-II. The other approaches are DCP [4], CAP [24], DehazeNet [8], image dehazing using residual-based deep CNN(RBDC) [25], GMAN [3] and FWBNET [15].

V. Conclusion

In this paper, a novel fusion-based model of ASM and NonASM models for SID is proposed. The proposed scheme takes a HI as input and produces a HFI as an output. The scheme has three parts in the first part a series of three carefully designed auto-encoders are presented with a PN. A detail reconstruction of haze-free image from input haze image is presented.

In the second part, ASM model is presented which uses DCP for image reconstruction and in the last part, a fusion method based on DWT and cross-bilateral filter based image fusion is proposed to fuse the two images to get a final HFI. The first part of the scheme is only used for training the benchmark data sets. The experiments on benchmark data sets show that the proposed framework got good result with compair to most conventional and deep learning-based methods in terms of PSNR and SSIM metrics. NHASM with recurrence model may be explored for the future work of this paper.

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