Deep Residual Haze Network for Image De-Hazing and De-Raining

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***Abstract*—** *Image dehazing on a hazy image aims to remove the haze and make the image scene clear, which attracts more and more research interests in recent years. Most existing image dehazing methods use a classic atmospheric scattering model and natural image priors to remove the image haze. In this paper, we propose an end-to-end image dehazing model termed as DRHNet (Deep Residual Haze Network), which restores the haze-free image by subtracting the learned negative residual map from the hazy image. Specifically, DRHNet proposes a context-aware feature extraction module to aggregate the contextual information effectively. Furthermore, it proposes a novel nonlinear activation function termed as RPReLU (Reverse Parametric Rectified Linear Unit) to improve its representation ability and to accelerate its convergence. Extensive experiments demonstrate that DRHNet outperforms state-of-the-art methods both quantitatively and qualitatively. In addition, experiments on image deraining task show that DRHNet can also serve for image deraining. Experimental results obtain the better results when compared to the other system.*

I. INTRODUCTION

Image dehazing on a hazy image aims to remove the haze and make the image scene clear, which attracts more and more research interests in recent years. Most existing image dehazing methods use a classic atmospheric scattering model and natural image priors to remove the image haze. The goal of the image dehazing algorithm is to restore a hazy image to a clear image, which has received significant research interest because various advanced image processing tasks require a clear scene. Traditional image dehazing algorithms are dedicated to accurately estimate the transmission and the global atmospheric light in hazy images, and then use the atmospheric scattering model to restore haze-free images. To overcome the problem mentioned above, we propose a Deep Residual Haze Network (DRHNet) that does not require the estimation of the system. The primary purpose of DRHNet is to learn the residual between the haze-free image and the hazy image, rather than learning the haze-free image directly. The benefits of this approach are as follows. First, optimizing the residual mapping is more straightforward than optimizing the original mapping. In the image dehazing task, the residuals between the haze-free image and the hazy image can be thought of as the residual mapping. Second, the complexity of the residual is much lower than the of the haze-free image, so the deep learning network is easier to fit the residual. Third, since the proposed DRHNet is not need the atmospheric scattering model for image dehazing, it can not only process image dehazing task, but also be used for other image enhancement tasks. Fourth, the residual can accurately determine the extent of different regions of the image affected by the haze. The experiment demonstrates that the proposed DRHNet surpasses other leading dehazing algorithms both in quantitative evaluation and qualitative evaluation. The contributions of this paper are, we propose a novel end-to-end image dehazing network called the DRHNet to restore the haze-free image by subtracting the estimated negative residual map from the hazy image. The negative residual map can reflect the extent of haze damage and the dehaze effect explicitly. Moreover, a novel activation function, called the reverse parametric rectified linear unit (RPReLU), is designed to improve the representation ability of the dehazing model and accelerate the convergence of the training. We conduct extensive experiments on multiple real-world datasets, and the results demonstrate DRHNet's effectiveness compared to other state-of-the-art baselines. We also apply the proposed DRHNet for image deraining task, and the results show that DRHNet outperforms the other state-of-the-art image deraining method of the system.

1.1 Image Dehazing

Image dehazing is a challenging problem in the field of computer vision. The purpose of Image dehazing is to recover a clear image from one single noisy frame caused by haze, fog or smoke. Image dehazing is a challenging problem in the field of computer vision. The purpose of Image dehazing is to recover a clear image from one single noisy frame caused by haze, fog or smoke. Haze is an atmospheric phenomenon that obscures the clarity of the sky. All the atmospheric particles are in the range below of 1000 m. Atmospheric particles are fog, moisture, smoke, water droplets, dust, etc. Haze is caused by atmospheric particles suspended in the air. It occurs in many populated areas like industrial areas. Due to haze clarity of images will be degraded. Haze is a combination of two components Air light and Direct attenuation of the system. While capturing the outdoor image during bad weather condition, the radiance received by the camera from the scene is attenuated along the line of sight. The incoming light is mixed with the light coming from all other directions called the Air light. It adds whiteness in the image. And the second component Attenuation is the gradual loss in intensity. Due to this the there is significant decay in the color. Amount of scattering depends on the distance between the scene points and the camera. So, the degradation is spatially variable. Dehazing is highly required in consumer photography and computer vision applications. Because many computer vision applications are suffering from low- contrast scene radiance. For example, there is a problem of haze in under water images. There are many methods available to remove haze from outdoor image.

1.2 1.2 Image Deraining

Images captured in rainy days suffer from noticeable degradation of scene visibility. The goal of single image deraining algorithms is to generate sharp images from a rainy image input. Image deraining can potentially benefit both the human visual perception quality of images, and many computer vision applications, such as outdoor surveillance systems and intelligent vehicles. The single-image deraining is to restore the rain-free background scenes of an image degraded by rain streaks and rain accumulation. The early single-image deraining methods employ a cost function, where various priors are developed to represent the properties of rain and background layers. Single-image deraining methods step into a deep-learning era, and exploit various types of networks are convolutional neural networks, recurrent neural networks, generative adversarial networks. A single-image deraining is to estimate the rain-free background layer of an image degraded by rain streaks and rain accumulation. Unlike video deraining methods, which leverage temporal redundancy and dynamics of rain, single image deraining methods exploit the spatial information of neighboring pixels and the visual properties of rain and background scenes. Single image deraining regards an input image as a fusion of a background image, a transmission map, rain streaks, and atmosphere light.

1.3 DRHN

DRHNet (Deep Residual Haze Network), is used to restores the haze-free image by subtracting the learned negative residual map from the hazy image. The primary purpose of DRHNet is to learn the residual between the haze-free image and the hazy image, rather than learning the haze-free image directly. The benefits of the system are used to optimizing the residual mapping is more straightforward than optimizing the original mapping. In the image dehazing task, the residuals between the haze free image and the hazy image can be thought of as the residual mapping. The complexity of the residual is much lower than the haze-free image, so the deep learning network is easier to fit the residual. DRHNet is not need the atmospheric scattering model for image dehazing, it can not only process image dehazing task, but also be used for other image enhancement tasks. DRHNet algorithms are used to both in quantitative evaluation and qualitative evaluation. DRHNet to restore the haze-free image by subtracting the estimated negative residual map from the hazy image. The negative residual map can reflect the extent of haze damage and the dehazing effect explicitly. Moreover, a novel activation function, called the reverse parametric rectified linear unit (RPReLU), is designed to improve the representation ability of the dehazing model and accelerate the convergence of the training.

1.4 RPReLU

The **rectified linear activation function** or **ReLU** for short is a piecewise linear function that will output the input directly if it is positive, otherwise, it will output zero. It has become the default activation function for many types of neural networks because a model that uses it is easier to train and often achieves better performance. The rectifier is an activation function defined as the positive part of its argument of the system. Rectifying activation functions are used to separate specific excitation and unspecific inhibition in the neural abstraction pyramid, which was trained in a supervised way to learn several computer visions tasks. RPReLU (Reverse Parametric Rectified Linear Unit) is a nonlinear activation function is used to improve its representation ability and to accelerate its convergence of the system. A novel activation function is called the reverse parametric rectified linear unit (RPReLU). It is designed to improve the representation ability of the dehazing model and accelerate the convergence of the training. The size of the feature map of the next convolution is half of the size of the feature graph of the previous convolution. Generally, the pixel value of haze-free images is lower than that of the hazy images, but sometimes the opposite happens. Therefore, parametric rectified linear unit (PReLU) is used in this context-aware encoder component, because PReLU improves model fitting with nearly zero extra computational cost and keeps the areas of the negative axis of the system. The RPReLU is a novel activation function with certain advantages in image dehazing because it is based on some prior knowledge of hazy images. So, the PReLU is used to gradually replace the RPReLU in the context-aware encoder, transformation, and haze decoder.

II. Literature Survey

Reside: A Benchmark for Single Image Dehazing

B. Li, W. Ren, D. Fu, D. Tao (2017).

In this article, we present a comprehensive study and evaluation of existing single image dehazing algorithms, using a new large-scale benchmark consisting of both synthetic and real-world hazy images, called Realistic Single Image Dehazing (RESIDE). RESIDE highlights diverse data sources and image contents, and is divided into five subsets, each serving different training or evaluation purposes. To provide a rich variety of criteria for dehazing algorithm evaluation, ranging from full-reference metrics, to no-reference metrics, to subjective evaluation and the novel task-driven evaluation. Experiments on RESIDE sheds light on the comparisons and limitations of state-of-the-art dehazing algorithms, and suggest promising future directions.

Deep Joint Rain Detection and Removal from A Single Image.

W. Yang, R. T. Tan (2017).

In this article, we present a rain removal problem from a single image, even in the presence of heavy rain and rain streak accumulation. We add a binary map that provides rain streak locations to an existing model, which comprises a rain streak layer and a background layer. We create a model consisting of a component representing rain streak accumulation (where individual streaks cannot be seen, and thus visually similar to mist or fog), and another component representing various shapes and directions of overlapping rain streaks, which usually happen in heavy rain. Based on the model, we develop a multi-task deep learning architecture that learns the binary rain streak map, the appearance of rain streaks, and the clean background, which is our ultimate output. To handle rain streak accumulation (again, a phenomenon visually similar to mist or fog) and various shapes and directions of overlapping rain streaks, we propose a recurrent rain detection and removal network that removes rain streaks and clears up the rain accumulation iteratively and progressively. The evaluation on real images, particularly on heavy rain, shows the effectiveness of our models and architecture.

Joint Bi-Layer Optimization for Single-Image Rain Streak Removal

L. Zhu, C. Fu (2017).

In this article, we present a novel method for removing rain streaks from a single input image by decomposing it into a rain-free background layer B and a rain-streak layer R. A joint optimization process is used that alternate between removing rain-streak details from B and removing non-streak details from R. The process is assisted by three novel image priors. Observing that rain streaks typically span a narrow range of directions, we first analyze the local gradient statistics in the rain image to identify image regions that are dominated by rain streaks. From these regions, we estimate the dominant rain streak direction and extract a collection of rain-dominated patches. Next, we define two priors on the background layer B, one based on a centralized sparse representation and another based on the estimated rain direction. A third prior is defined on the rain-streak layer R, based on similarity of patches to the extracted rain patches. Both visual and quantitative comparisons demonstrate that our method outperforms the state-of-the-art.

Cleaning The Skies- A Deep Network Architecture for Single-Image Rain Removal

X. Fu, J. Huang, X. Ding, Y. Liao (2017).

In this article, we introduce a deep network architecture called DerainNet for removing rain streaks from an image. Based on the deep convolutional neural network (CNN), we directly learn the mapping relationship between rainy and clean image detail layers from data. To increase depth or breadth of the network, we use image processing domain knowledge to modify the objective function and improve deraining with a modestly sized CNN. Specifically, we train our DerainNet on the detail (high-pass) layer rather than in the image domain. Though DerainNet is trained on synthetic data, we find that the learned network translates very effectively to real-world images for testing. Moreover, we augment the CNN framework with image enhancement to improve the visual results. Compared with the state-of-the-art single image de-raining methods, our method has improved rain removal and much faster computation time after network training.

Dehazenet: An End-To End System for Single Image Haze Removal.

B. Cai, X. Xu, K. Jia, C. Qing (2016).

In this article, we demonstrated the end-to-end system called DehazeNet, for medium transmission estimation. DehazeNet takes a hazy image as input, and outputs its medium transmission map that is subsequently used to recover a haze-free image via atmospheric scattering model. DehazeNet adopts convolutional neural network-based deep architecture, whose layers are specially designed to embody the established assumptions/priors in image dehazing. Specifically, the layers of Maxout units are used for feature extraction, which can generate almost all haze-relevant features. We also propose a novel nonlinear activation function in DehazeNet, called bilateral rectified linear unit, which is able to improve the quality of recovered haze-free image. Experiments on benchmark images show that DehazeNet achieves superior performance over existing methods, yet keeps efficient and easy to use.

Single Image Dehazing Via Multi-Scale Convolutional Neural Networks

W. Ren, S. Liu, H. Zhang, J. Pan (2016)

In this article, we analyse a multi-scale deep neural network for single-image dehazing by learning the mapping between hazy images and their corresponding transmission maps. The proposed algorithm consists of a coarse-scale net which predicts a holistic transmission map based on the entire image, and a fine-scale net which refines results locally. To train the multi-scale deep network, we synthesize a dataset comprised of hazy images and corresponding transmission maps based on the NYU Depth dataset. Extensive experiments demonstrate that the proposed algorithm performs favorably against the state-of-the-art methods.

Dehazing With Improved Heterogeneous Atmosphere Light Estimation and A Nonlinear Color Attenuation Prior Model

S. Zhang, C. Qing, X. Xu (2016).

In this article, we demonstrated an improved heterogeneous atmosphere light estimation method and a novel depth estimation algorithm with Color Attenuation Prior (CAP) to dehaze single image. Firstly, it estimates the atmosphere light with mean-pooling on the illuminance component from HSV color space. The estimated atmosphere light is more robust because of its independence of a specified pixel. Secondly, the scene depth is estimated by a nonlinear CAP model which can overcome the defects of the occurrence of negative scene depths from the linear CAP model. Experimental results demonstrate that the proposed algorithm outperforms the state-of-the-art methods in dehazing images.

Robust Image and Video Dehazing with Visual Artifact Suppression Via Gradient Residual Minimization.

C. Chen, N. Do (2016).

In this article, we analyse a new method for reliable suppression of different types of visual artifacts in image and video dehazing. Our method makes contributions in both the haze estimation step and the image recovery step. Firstly, an image-guided, depth-edge-aware smoothing algorithm is proposed to refine the initial atmosphere transmission map generated by local priors. In the image recovery process, we propose Gradient Residual Minimization (GRM) for jointly recovering the haze-free image while explicitly minimizing possible visual artifacts in it. Our evaluation suggests that the proposed method can generate results with much fewer visual artifacts than previous approaches for lower quality inputs such as compressed video clips.

Rain Streak Removal Using Layer Priors

Y. Li, R. Tan, X. Guo (2016).

In this article, we present an effective method that uses simple patch-based priors for both the background and rain layers. These priors are based on Gaussian mixture models and can accommodate multiple orientations and scales of the rain streaks. This simple approach removes rain streaks better than the existing methods qualitatively and quantitatively.

Removing Rain from A Single Image Via Discriminative Sparse Coding

Y. Luo, Y. Xu (2015).

In this article, we present a dictionary learning based algorithm for single image de-raining. The basic idea is to sparsely approximate the patches of two layers by very high discriminative codes over a learned dictionary with strong mutual exclusivity property. Such discriminative sparse codes lead to accurate separation of two layers from their non-linear composite. The experiments showed that the proposed method outperformed the existing single image de-raining methods on tested rain images.

Problem Definition: Image dehazing on a hazy image aims to remove the haze and make the image scene clear, which attracts more and more research interests in recent years. Most existing image dehazing methods use a classic atmospheric scattering model and natural image priors to remove the image haze.

Drawbacks: A CNN to precisely estimate the transmission. Although these algorithms based on CNNs can estimate less accurately compared with our proposed method, it still needs to estimate more accurately to recover the haze free image perfectly.

- Less Performance
- Low Efficiency

III. PROPOSED WORK

Image dehazing on a hazy image aims to remove the haze and make the image scene clear, which attracts more and more research interests in recent years. Our aims to remove the haze and make the image scene clear, an end-to-end image dehazing model termed as DRHNet (Deep Residual Haze Network), which restores the haze-free image by subtracting the learned negative residual map from the hazy image. DRHNet proposes a context-aware feature extraction module to aggregate the contextual information effectively. Furthermore, it proposes a novel nonlinear activation function termed as RPReLU (Reverse Parametric Rectified Linear Unit) to improve its representation ability and to accelerate its convergence. Extensive experiments demonstrate that DRHNet outperforms state-of-the-art methods both quantitatively and qualitatively. In addition, experiments on image deraining task show that DRHNet can also serve for image deraining.

Advantages

- Accurate
- More Effective
- Better performance
- High Efficiency

3.1 Input Haze Image

A collect a dataset that contains a large number of hazy/clear/transmission-map image pairs, training and test datasets are synthesized and obtained in the input haze image. All the training and test samples are obtained from the NYU Depth dataset in a similar way, a test dataset consisting of 300 images is obtained. We ensure that none of the training images are in the test set. By varying A and β, we generate our training data with a variety of different conditions. The image content is independent of its corresponding depth. Even though the training images are from the indoor dataset and depths of all the images are relatively shallow, we could modify the value of the attenuation coefficient β to vary the haze concentration to make sure the datasets can also used for outdoor image dehazing. Meanwhile, the experimental results have also demonstrated the effectiveness of discussed training datasets.

3.2 Design of The Context-Aware Encoder

The context-aware feature extraction module has been proposed to make DRHNet (Deep Residual Haze Network) to extract features effectively. In this section, they consider both the context-aware feature extraction module and context-aware encoder component are used the process of the system.

3.2.1 Context-Aware Feature Extraction Module

The most significant characteristic of hazy image is that different regions of the hazy image are affected by different degrees of haze, but the influence degree of each pixel affected by haze is very close to its surrounding areas. Therefore, it to use multi-scale convolution to extract the features of hazy image. To aggregate the contextual information, the context-aware encoder component is used.

3.2.2 Context-Aware Encoder Component

Image dehazing is an important image processing task that has high requirements on the integrity of the spatial image information. In the first layer of the proposed DRHNet, we adopt the context-aware feature extraction module to aggregate the contextual information. The next layer is obtained from the previous layer by the convolution with a kernel size. There are only three-layer convolutions in the context-aware encoder component. The size of the feature map of the next convolution is half of the size of the feature graph of the previous convolution. Generally, the pixel value of haze-free images is lower than that of the hazy images, but sometimes the opposite happens. Therefore, reverse parametric rectified linear unit (RPRelu) is used in this context-aware encoder component, because RPRelu improves model fitting with nearly zero extra computational cost and keeps the areas of the negative axis.

3.3 Transformation Component

The depth of CNN has a significant influence on the dehazing networks' performance. It provides a large number of experiments to prove that the strategy of adopting building blocks to extract features is easier to optimize deep networks. To improve the performance of the DRHNet, the building blocks are used in the transformation component to learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. In the part, we will explore the best trade-off between the performance and the number of parameters.

3.3.1 Reverse parametric rectified linear unit (RPRelu)

RPRelu is useful to the proposed DRHNet and the effectiveness result has been validated. the residual obtained from DRHNet should be a negative matrix. Based on this prior knowledge, we maintain the original signal strength in the negative part of the activation function and suppress the original signal by adding coefficients in the positive part.

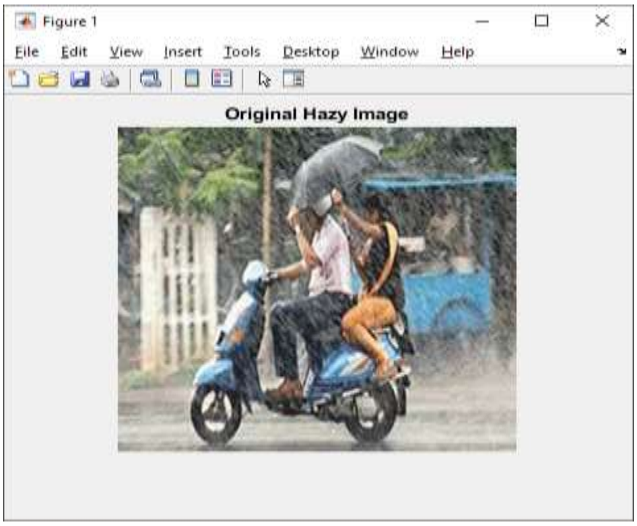
3.4 Haze Decoder Component

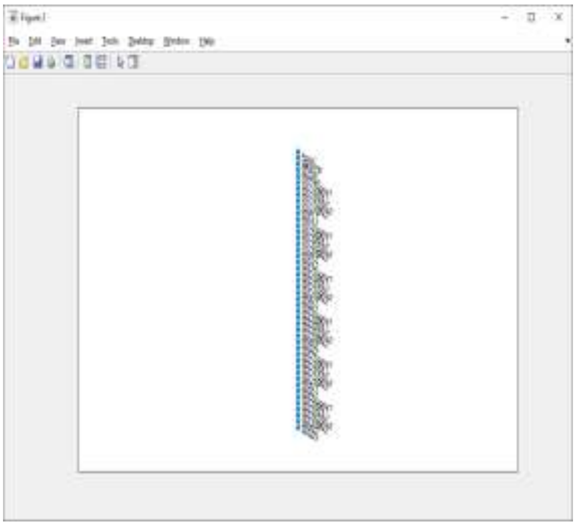
The motivation of the DRHNet is to learn the residual between the haze-free image and the hazy image accurately. It is necessary to concatenate the features obtained by the haze decoder component with features obtained by haze decoder component. RPRelu is also used in the haze decoder component because the primary purpose of haze decoder is to estimate the residual map from high-level features obtained from the transformation component. Because the structure of the proposed DRHNet is symmetric, the other parameters of the haze decoder component are set the same as the context-aware encoder component. Finally, the haze decoder component outputs the residual between hazy and haze-free image and uses the residual map and the original input hazy image to obtain the dehazed image.

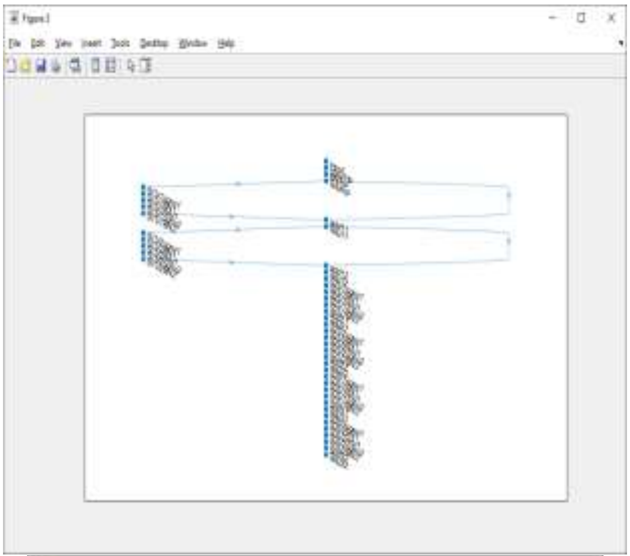
3.5 Output Haze Image

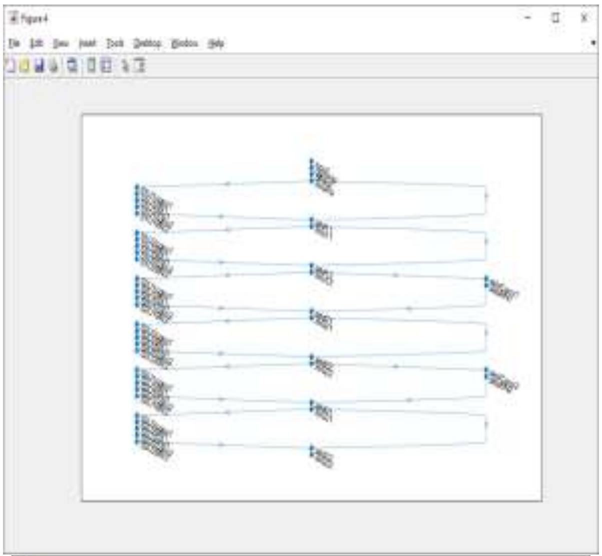
Output haze image is finally predicting the output based on the Haze deraining and Haze dehazing. The experimental results prove that the proposed DRHNet has the best performance when RPRelu is used in a context-aware encoder component, and RPReLU is used in the transformation component and haze decoder component is obtained in the output layer.

IV. IMPLEMENTATION









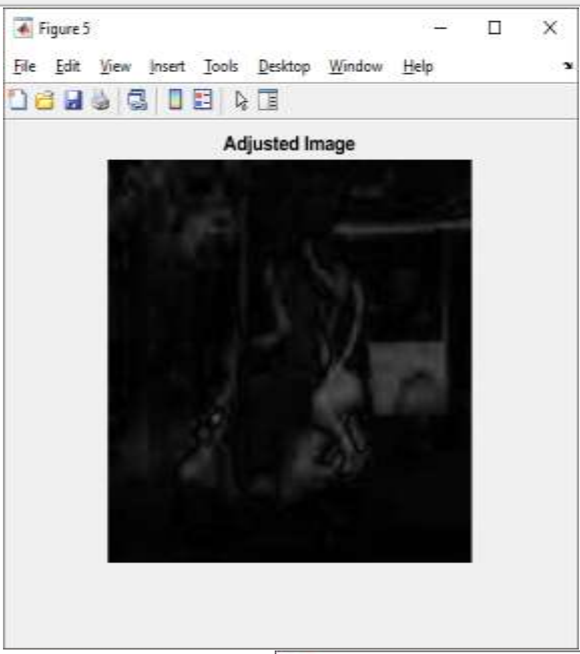


Figure 5
File Edit View Insert Tools Desktop Window Help
Adjusted Image

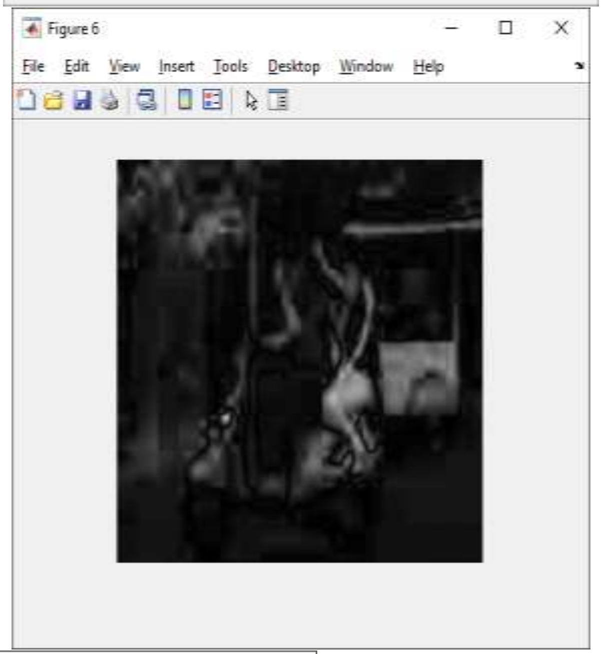


Figure 6
File Edit View Insert Tools Desktop Window Help

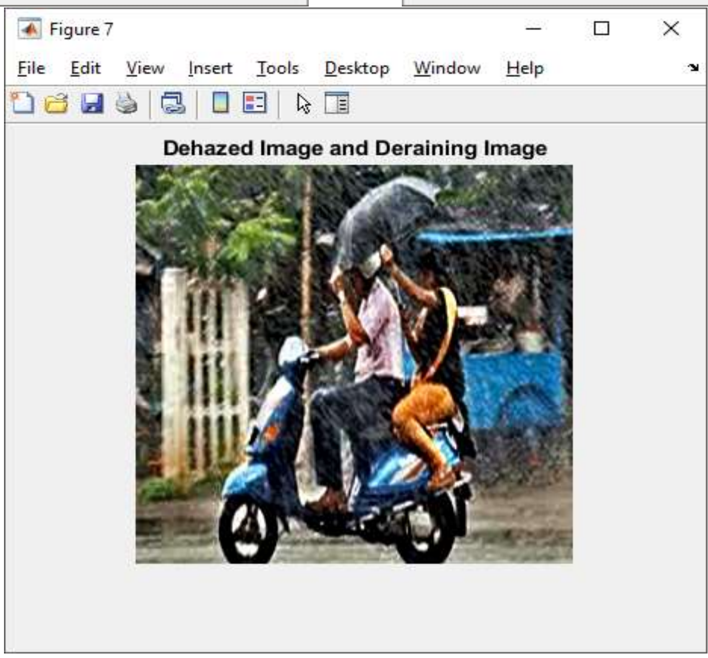


Figure 7
File Edit View Insert Tools Desktop Window Help
Dehazed Image and Deraining Image

V. CONCLUSION

To overcome the problem of the system, we propose a Deep Residual Haze Network (DRHNet) that does not require the estimation of system. The primary purpose of DRHNet is to learn the residual between the haze-free image and the hazy image, rather than learning the haze-free image directly. The benefits of this approach demonstrated, that optimizing the residual mapping is more straightforward than optimizing the original mapping. In the image dehazing task, the residuals between the haze-free image and the hazy image can be thought of as the residual mapping. The complexity of the residual is much lower than the of the haze-free image, so the deep learning network is easier to fit the residual. Since the proposed DRHNet does not need the atmospheric scattering model for image dehazing, it can not only process image dehazing task, but also be used for other image enhancement tasks. So, the residual can accurately determine the extent of different regions of the image affected by the haze. The image dehazing and deraining performance of the proposed DRHNet. In our article, we proposed a novel end-to-end deep residual haze network termed as DRHNet for single image dehazing and deraining. DRHNet designed a context-aware feature extraction module to aggregate the contextual information more effectively and proposed a novel activation function called RPReLU to accelerate the convergence of DRHNet. Experiments results demonstrated the superiority of DRHNet over the counterparts. In addition, experiments on the image deraining dataset also demonstrated its significant improvement of performance on image deraining. In the future, we are interested in the researches on general deep learning networks for a variety of image restoration tasks, or on extension of the network for video dehazing task.

Future Enhancement

- In addition, experiments on the image deraining dataset also demonstrated its significant improvement of performance on image deraining.
- In the future, we are interested in the researches on general deep learning networks for a variety of image restoration tasks, or on extension of the network for video dehazing task.

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