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Research Article

Multi-Scale Deep Residual Learning-based Single Image Haze Removal

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Abstract

Images captured from outside visible devices are generally degraded by way of turbid media, including haze, fog, rain, and snow. Haze adversely degrades the quality of an image. Because of the weather conditions, haze is the most typical one in outdoor scenes. Due to the ill-posed nature of single images, dehazing them might be difficult. In this, a deep learning-based architecture that is denoted by MSRL Dehaze Net for single image haze removal is counting on multi-scale residual learning (MSRL). Haze removal in base can be achieved by multi-scale residual learning and simplified U-Net learning for mapping between hazy and haze-free components. The resulted dehazed image is obtained by the haze-removed base and also enhanced detail image components. This dehazed result passes through the clahe method for enhancement and obtained better final dehazed results. Experimental results have demonstrated and compared with other approaches such as Dark Channel Prior and Dehazing using GAN.
Keywords: *MSRL dehaze net, clahe, dark channel prior, GAN.*

Abbreviations

AHE - Adaptive Histogram Equilization, CLAHE - Contrast Limited Adaptive Histogram Equilization, DCP - Dark Channel Prior, FSIM - Feature based Similarity Index Measure, GAN - Generative Adversarial Network, HF - High Frequency, LF - Low Frequency, MSRL - Multi Scale Residual Learning, OTS - Outdoor Training Set, PSNR - Peak Signal to Noise Ratio, RMSE - Root Mean Square Error, SSIM - Structural Similarity Index Measure.

Introduction

Under severe weather conditions, images captured from outdoor scenes can be affected by haze, smog etc. To achieve single image dehazing, the atmospheric scattering model has been commonly used to describe the image formation in the presence of haze. In this model, a hazy image is formulated as

$$I(X) = J(X)t(x) + A(1 t(x)) \qquad (1)$$

where I is the observed hazy image, J is the scene radiance, t is the medium transmission, A is the global atmospheric light, and x indicates the index of a pixel. Image dehazing using a deep convolutional neural network architecture for single image dehazing, that is denoted by the multi-

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scale deep residual learning-based single image dehazing network (MSRL-DehazeNet). This method decomposes each image into the base component and detail component. Base component including the color information and the detail component including the texture information. Only the base component of each image is used for deep dehazing model learning. The MSRL Dehaze Net aims at learning multi-scale features for base image component restoration with preserving better color information. The detail image component is enhanced by the deep model for enhancement factor prediction. Therefore, this method would learn better color information than current deep learning based approaches for hazy image restoration. Base dehazed output with the integration of enhanced detail information, produce dehaze output. That is further fed to clathe method for enhancement and obtain better dehazing results.

Literature Survey

Some of the initial work on dehazing involves the use of classical image enhancement techniques such as histogram processing, contrast and saturation-based processing to im-prove the visibility of hazy images. Most of the methods follow the physical atmospheric scattering model and attempt to recover better scene radiance. There are many methods employed on multiple images to improve the performance. He et al. in [2] proposed a dark-channel model to estimate the transmission map which is based on the observation that in case of haze-free image patches, at least one color channel has some pixels with very low intensities. In the haze image, the intensity of these dark pixels in that channel is mainly contributed by the air light and hence, these dark pixels can directly provide accurate estimation of the transmission map. To improve the computational efficiency of the dark channel prior-based method, standard median filtering, median of median filter and guided image filter are used to replace the time-consuming soft matting [2]. Ren et al. [4] proposed a multi-scale deep neural network to learn the mapping between hazy images and their corresponding transmission maps. Gated Fusion Network for Single Image Dehazing [6] trainable neural network that consists of an encoder and a decoder. The encoder is to capture the context of the derived input images. The decoder is to estimate the contribution of each input to the dehazed result by using the learned representations attributed to the encoder. A fusion-based strategy that derives three inputs from an original hazy image by applying WB (White Balance), CE (Contrast Enhancing), and GC (Gamma Correction). Finally the dehazed image is obtained by gating the important features of the derived inputs. Derive several inputs based on observations. First one is the colours in hazy images change due to the influence of the atmospheric light. The second one is the lack of visibility in distant regions due to scattering and attenuation phenomena. Based on these observations, can generate three inputs that recover the colour and visibility of the entire image from the original hazy image. A non-local prior used [7] is based on the assumption that colors of Dehazed image are approximated by a few hundred distinct colors forming tight clusters in RGB space. To predict the hazy density of an image, three haze-relevant statistical image features was derived in to develop a haze density evaluator for single image haze removal.

Multi-Scale Deep Residual Learning Network for Single Image Dehazing

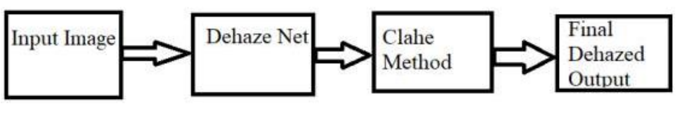

Fig. 1. Overall Block Diagram of Dehaze Net with Clahe Method

Multi-scale deep residual learning-based single image haze removal consists of preprocessing stage by image decomposition, the dehazing stage that is relying on MSRL Dehaze Net (multi-scale deep residual convolutional neural network) to produce the dehaze base image component, the generation stage of haze removed image by integrating the dehazed base image component and the detail enhanced image component.

A. Preprocessing Stage

First an input hazy image is decomposed into the base component and the detail component by image filtering. The base component of a hazy image refers to the low-frequency (LF) part of the image and the another component that is detail component of the image refers to the high frequency (HF) part of the image. The base part have most basic information that will be retained in the LF component while the details and the other edge or texture information will be included in the HF component of the image.

B. Learning Multi-Scale Deep Residual CNN and Simplified U-Net for Haze Removal of Base Image Component

Structured feature extraction, statistical feature extraction, and image regression are the three aspects of the MSRL-DehazeNet.

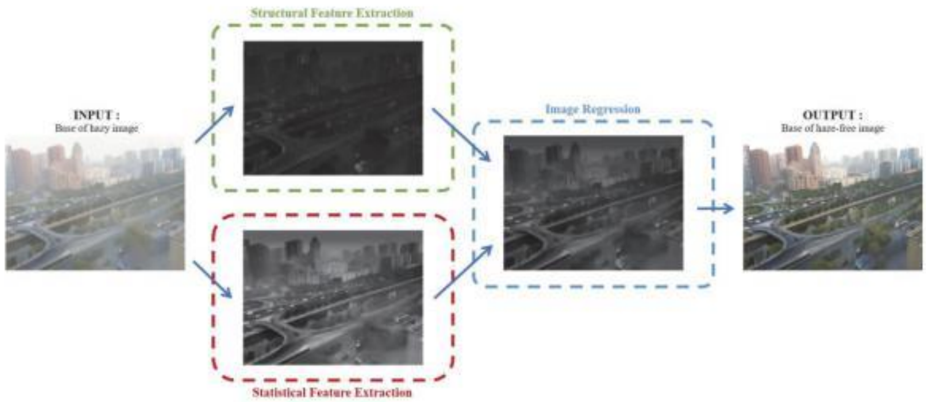

Fig. 2. Visualization of MSRL Dehaze Net for Single Image Haze Removal

Structural feature extraction is the first part consists of seven layers. The activation function as RELU for all convolutional operations in the initial section of MSRL-DehazeNet. The multi-scale convolutional neural network architecture each convolution layer includes two sublayers of different kernel sizes that would be useful to learn multi-scale haze-relevant structural features and also would be helpful for image haze removal. To avoid the problem of color distortion in a dehazed image, the feature maps created by each previous layer are entirely preserved and fed into the following layer.

Statistical feature extraction is the second part that is simplified U-Net, which consists of eight layers. U-Net is used for learning the common feature extraction. For an input image in the simplified U-Net architecture, the spatial information is reduced while feature information is increased during the contraction path. During the expanding path, high-resolution features from the contracting path are joined with feature and spatial information through a series of deconvolution and concatenation operations. The contracting path of simplified U-Net first consists of two convolutional layers of different number of filters and kernel sizes. Each one is followed by a ReLU as activation function and max pooling operation for down sampling. Then, a convolutional layer with 32 filters is used. The expansive path of the simplified U-Net consists of two up-sampling steps, each of which includes a deconvolutional layer, followed by a concatenation layer with the down-sampled feature maps from the contracting path. Between the two up-sampling steps is a convolutional layer with 16 filters is used. This architecture would be helpful for extraction of haze-relevant statistical image features.

Image regression is the third part used for converting the feature channels from the two previous parallel paths for feature extractions of structural and statistical features into the haze removed base component.

C. Reconstruction of Haze-Removed Image

The haze-removed or dehazed image is obtained by the haze-removed base and the enhanced detail image components. The deep factor prediction convolutional neural network consists of two convolutional layers, followed by a mean operation. The mean operation calculates the mean value of all of the elements of the tensor consisting of the feature maps from the previous layer. As a result, the predicted enhancement factor for detail image component enhancement can be determined by computing the mean value of all elements from the input feature map.

Contrast Limited Adaptive Histogram Equalization

Ordinary AHE (Adaptive Histogram Equalization) tends to amplify contrast in image regions that are almost constant. This is mainly developed for the enhancement of low contrast images. CLAHE (Contrast Limited Adaptive Histogram Equalization) is a variant of adaptive histogram equalization in which the contrast amplification is limited. The contrast limited procedure has to be applied for each neighbourhood from which a transformation function is derived in clahe. In clahe, rather than taking the whole image, it prevents over amplification by dividing the image into small data regions that are called tiles and then it performs contrast enhancement. Overall enhanced image is obtained by rejoining these tiles. It is applied over both type of images that are gray scale and coloured images. Dehazed result from Dehaze Net is fed to the clahe method, and generate final dehazed output with better result.

Fig. 3. Dehazed Image by Using Clahe Enhancement

Experimental Results and Comparison wıth Different Approaches

The OTS (Outdoor Training Set) from the RESIDE dataset with a wide variety of scenes was used to train the MSRL-DehazeNet.

A. Dark Channel Prior (DCP) for Single Image Haze Removal

The dark channel prior is based on outdoor haze-free image statistics. In at least one colour channel (RGB), the majority of the local regions in an image that do not cover the sky, and certain pixels known as dark pixels, have very low intensity approximations to zero. The DCP is an approximation to zero for the image pixel value of the dark channel.

Fig. 4. Hazy Image and Dehazed Image by Dehaze Net

Images having the low intensity in the dark channel is mainly due to three factors that are shadows, colorful objects or surfaces, dark objects or surfaces. The four key processes in DCP dehazing are: first is estimation of atmospheric light, second is transmission map estimation, third is the transmission map refinement, and fourth one is image reconstruction. In hazy images, airlight contributes significantly to the intensity of dark pixels in the channel. As a result, these dark pixels can provide a direct estimate of haze transmission. Pixels with values much above zero are produced by the dark channels in hazy images. Because atmospheric light is intense and achromatic, a combination of airlight and direct attenuation increases the minimum value of the three colour channels, RGB, in the nearby patch greatly. This means that the dark channel's pixel values can be used to determine haze density in an image.

Fig. 5. Hazy Image and Dehazed Image by Dark Channel Prior

B. GAN based Dehazing

A Generative Adversarial Network (GAN) is a kind of neural network architecture structure for generative modeling. A GAN is a generative model that uses two neural network models to train it. The role of a network termed generator is to generate new images from some input using learned parameters. The discriminator network is the other one. The function of discriminator is to distinguish whether the input image is true or fake. During a test phase, the input of GAN network is a hazy image and the final output is dehazed image. The discriminator identifies whether the input is a real clear image or a generated clear image. Discriminator is trained for one or more epochs using real and fake images. When the discriminator can no longer distinguish between actual and fake images, the process approaches equilibrium. Hazy image with the dehaze image as real data and hazy image with generated output as fake data.

The peak signal-to-noise ratio (PSNR) is the ratio of a signal's maximum achievable power to the power of corrupting.

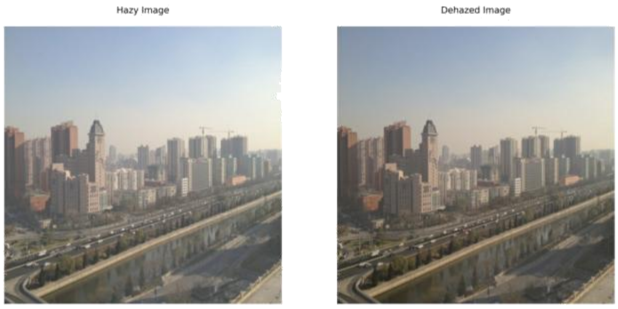

Fig. 6. Hazy Image and Dehazed Image by GAN based Dehazing

Table I

Quantitative Results of Different Approaches

APPROACHES	PSNR	SSIM	RMSE	FSIM
DEHAZE NET WITH CLAHE	45.99	0.976	0.0050	0.8864
DEHAZE NET	42.79	0.947	0.0090	0.8347
DARK CHANNEL PRIOR	35.22	0.792	0.01923	0.8152
GAN BASED DEHAZING	36.45	0.814	0.0097	0.8263

noise that influences the constancy of its illustration. PSNR is commonly stated as a logarithmic quantity on a decibel scale.

The structural similarity index measure (SSIM) is a tool for determining how similar two images are.

The root-mean-square error (RMSE) is a measure of how close a model's predicted values are to the actual values. It's always a positive. In general, a smaller RMSE is preferable to a greater one. RMSE is the square root of the average of square errors.

A Feature-based Similarity Index Measure (FSIM) is a method for determining image similarity. FSIM is primarily based on two basic features: Phase Congruency (PC), which is the primary feature, and Gradient Magnitude (GM), which is the secondary characteristic.

From the table, it is observed that Dehaze Net with clahe have higher PSNR, SSIM, RMSE, FSIM values as compared to other approaches. Therefore this method produce better dehazed results.

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Conclusion

Multi-scale deep residual Convolutional Neural Network architecture, called MSRL-DehazeNet, for single image haze removal is discussed and this method first decomposes an input hazy image into the base components and its detail components. The base component is fed to the multi-scale neural network with deep residual learning and simplified U-Net learning to obtain the haze-removed base component by extracting the haze-relevant structural and statistical image features for preserving the colour information of the image. The detail component is also enhanced. The dehazed result obtained from the base dehazed component with detail enhancement passes through the clahe method and produce final dehazed result. Experimental results show that by using this method achieves better or comparable haze removal performance with other image dehazing algorithms.

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