Image Dehazing

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***Abstract*—Single image haze removal is a challenging ill-posed problem. Existing methods use various priors and neural networks to get plausible dehazing solutions. The key to achieve haze removal is to estimate a medium transmission map for an input hazy image. In this paper, we adopt five image dehazing methods, including Dark Channel Prior method, Color Attenuation Prior method, DehazeNet method, Single Image Dehazing via MSCNN method, and Non-Local Image Dehazing method. To evaluate and compare the performance of these five methods, we apply three evaluation measures — Mean Squared Error (MSE) , Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM).**

I. Introduction

Haze is a traditional atmospheric phenomenon where dust, smoke and other dry particles obscure the clarity of the atmosphere. Haze removal is a challenging problem because the haze transmission depends on the unknown depth which varies at different positions.

Single image haze removal has made significant progresses recently, due to the use of better assumptions and priors. Haze removal from a single image is a difficult vision task. In contrast, the human brain can quickly identify the hazy area from the natural scenery without any additional information.

In recent years, plenty of efforts have been focusing on the image dehazing process. Numbers of different image dehazing techniques are presented, but there is not even a one single method to be considered as a best method for different kind of images, only suitable for one specific type of images. Hence, image dehazing is still a difficult task in computer vision.

The outline of the paper is as follows. In Section 2, the background of the image dehazing are described. In Section 3, the theoretics of the five methods we adopt are briefly reviewed. In Section 4, three quantitative metrics of the dehazing quality are described. The performances of five dehazing techniques are analyzed in Section 4. Section 5 draws the conclusion.

II. Background

In computer vision and computer graphics, the model widely used to describe the formation of a hazy image is

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

where I is the observed intensity, J is the scene radiance, A is the global atmospheric light, and t is the medium transmission describing the portion of the light that is not scattered and reaches the camera. The goal of haze removal is to recover J, A, and t from I. For an N-pixel color image I, there are $3N$ constraints and $4N$+3 unknowns. This makes the problem of haze removal inherently ambiguous.

In the formula, the first term $J(x)t(x)$ on the right-hand side is called direct attenuation, and the second term $A(1 - t(x))$ is called airlight. The direct attenuation describes the scene radiance and its decay in the medium, and the airlight results from previously scattered light and leads to the shift of the scene colors. While the direct attenuation is a multiplivative distortion of the scene radiance, the airlight is an additive one. When the atmosphere is homogenous, the transmission t can be expressed as

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

where β is the scattering coefficient of the atmosphere and d is the scene depth. This equation indicates that the scene radiance is attenuated exponentially with the depth. If we can cover the transmission, we can alse recover the depth up to an unknown scale.

As multiple solutions exist for a given hazy image, this problem is highly ill-posed. If we know the t and A, we can recover J in the hazy image.

III. Methods

In this Section, we briefly review the following five image dehazing methods:

- Dark Channel Prior method [4]
- Color Attenuation Prior method [5]
- DehazeNet method [3]
- Single Image Dehazing via MSCNN method [6]
- Non-Local Image Dehazing method [2]

A. Dark Channel Prior method

The work observed an interesting phenomenon of outdoor natural scenes with clear visibility. The dark channel prior is based on the following observation on outdoor haze-free images: In most of the nonsky patches, at least one color channel has some pixels whose intensity are very low and close to zero [4]. Equivalently, the minimum intensity in such a patch is close to zero. The paper defined the concept of a dark channel. For an arbitrary image J, its dark channel J^{dark} is given by

$$J^{dark}(x) = \min_{y \in \Omega(x)} \left(\min_{c \in \{r,g,b\}} J^c(y) \right) \tag{3}$$

where J^c is a color channel of J and $\Omega(x)$ is a local patch centered at x. A dark channel is the outcome of two minimum operators are commutative.

Using the concept of a dark channel, the author found that if J is an outdoor haze-free image, except for the sky region, the intensity of J's dark channel is low and tends to be zero:

$$J^{dark} \to 0. \tag{4}$$

We call the observation dark channel prior.

The dark channel prior is used to estimate the transmission as follows. Based on the Atmospheric Scattering Model. We can express:

$$\frac{I^c(x)}{A^c} = t(x)\frac{J^c(x)}{A^c} + 1 - t(x). \tag{5}$$

Assuming that we work on a local patch, $\Omega(x)$ and t(x) are constant within the patch, $\tilde{t}$(x), then we can be writen as:

$$\min_{y\in\Omega(x)}\left(\min_c \frac{I^c(x)}{A^c}\right) = \tilde{t}(x) \min_{y\in\Omega(x)}\left(\min_c \frac{J^c(x)}{A^c}\right) + 1 - \tilde{t}(x). \tag{6}$$

and consequently, due to the dark channer prior:

$$\tilde{t}(x) = 1 - \omega \min_{y\in\Omega(x)}\left(\min_c \frac{I^c(x)}{A^c}\right) \tag{7}$$

where A^c is obtained by picking the top 0.1% brightest pixels in the dark channel. Finally, to have a smooth and robust estimation of $t(x)$ that can avoid the halo effects due to the use of patches, ω is a cofficient of a range of $[0, 1]$, the method employs the closed-from solution of matting.

B. Color Attenuation Prior method

The paper proposed a novel linear color attenuation prior, based on the difference between the brightness and saturation of the pixels within the hazy image. By creating a linear model for the scene depth of hazy image with this simple but powerful prior and learning the parameters of the model using a supervised learning method, the depth information can be well recovered. By means of the depth map obtained by the proposed method, the scene radiance of the hazy image can be recovered easily [5].

Since the concentration of haze increases along with the change of the scene depth in general, the author make an assumption that the depth of the scene is positively correlated with the concentration of the haze:

$$d(x) \propto c(x) \propto v(x) - s(x) \tag{8}$$

where d is the scene depth, c is the concentration of the haze, v is the brightness of the scene and s is the saturation.

The paper create a linear model, a more accurate expression, as follows:

$$d(x) = \theta_0 + \theta_1 v(x) + \theta_2 s(x) + \varepsilon(x) \tag{9}$$

where x is the position within the image, d is the scene depth, v is the brightness component of the hazy image, s is the saturation component, θ_0, θ_1, θ_2 are the unknown linear

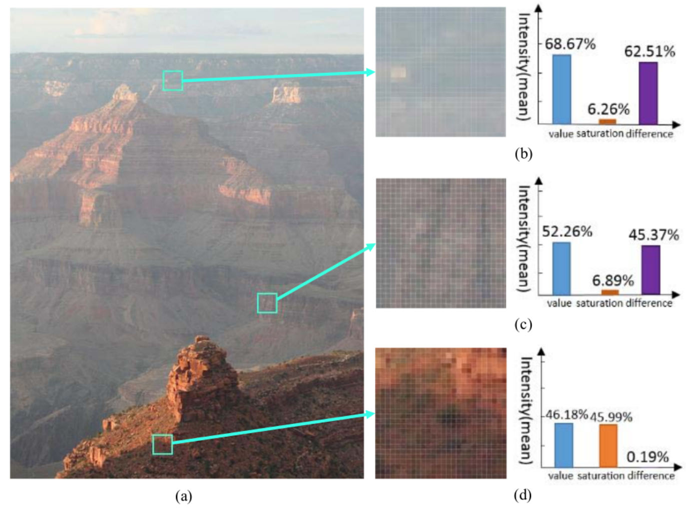

Fig. 1. The concentration of the haze is positively correlated with the difference between the brightness and the saturation. (a) A hazy image. (b) The close-up patch of a dense-haze region and its histogram. (c) The close-up patch of a moderately hazy region and its histogram. (d) The close-up patch of a haze-free region and its histogram.

coefficients, $\varepsilon(x)$ is a random variable representing the random error of the model, and ε can be regarded as a random image. According to the property of the Gaussian distribution, a more expression, as follows:

$$d(x) \sim p(d(x)|x, \theta_0, \theta_1, \theta_2, \sigma^2) = N(\theta_0 + \theta_1 v + \theta_2 s, \sigma^2). \tag{10}$$

It can use a simple and efficient supervised learning method to determine the coefficients. If we calculate the $d(x)$, it can get the depth map that recovered. Based on the atmospheric scattering model, we need to estimate the A in the model, it can get the clear image we need.

C. DehazeNet method

The paper proposed a learning based framework similar to that trains a regressor to predict the tranmission value $t(x)$ at each pixel (16×16) from its surrounding patch [3].

Unlike the used hand crafted feature, the paper applied a convolutional neural network (CNN) based architecture with special network design (See for the architecture). The network, termed DehazeNet, are conceptually formed by four sequential operations (feature extraction, multi-scale mapping, local extremum and non-linear regression), that consists of 3 convolution layers, a max-pooling, a Maxout unit and a Bilateral Rectified Linear Unit (BReLU, a nonlinear activation function extended from standard ReLU). The training set that they gathered haze free patches from Internet to generate hazy patches using the hazy imaging model with random transmissions t and assuming white atmosphere light color (A^c= $[111]^T$). Once all the weights in the network are obtained from the training, the transmission estimation for a new hazy image patch is simply forward propagation using the network. To handle the block artifact caused by the patch based estimation, guided filtering is used to refine the transmission map.

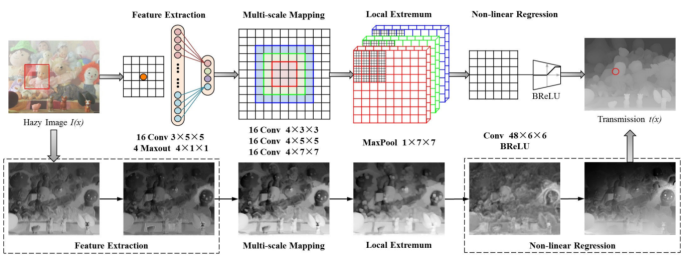

Fig. 2. The architecture of DehazeNet. DehazeNet conceptually formed by four sequential operations (feature extraction, multi-scale mapping, local extremum and non-linear regression), which is constructed by 3 convolution layers, a max-pooling, a Maxout unit and a Bilateral Rectified Linear Unit activation function.

D. Single Image Dehazing via MSCNN method

The paper proposed the image dehazing problem via a multi-scale deep network which learns effective features to estimate the scene transmission of a single haze image. It proposed feature learning method is easy to implement and reproduce. The network, called MSCNN. In the proposed multi-scale model, the method used a coarse-scale network to learn a holistic estimation of the scene transmission, and then use a fine-scale network to refine it using local information and the output from the coarse-scale network(See for the architecture) [6].

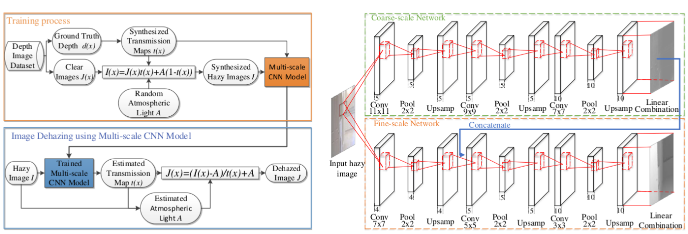

Fig. 3. The architecture of MSCNN. The main steps of the proposed algorithm and the architecture of the proposed multi-scale CNN for learning haze-relevant features.

In the coarse-scale network, the key observation is that image content is independent of scene depth and medium transmission, the same image (or patch) content can appear at different depths in different images. Therefore, although the training images have relatively shallow depths, the author could increase the haze concentration by adjusting the value of the medium extinction coefficient β. Based on this premise, the synthetic transmission maps are independent of depth $d(x)$ and cover the range of values in real transmission maps. In the fine-scale network, it can help estimate scene transmission maps. The transmission map from the coarse-scale network serves as additional features in the fine-scale network, which greatly improve the final estimation of scene transmission map. The network architecture is compact and robost for image dehazing.

E. Non-Local Image Dehazing method

The paper proposed an algorithm based on a new, non-local prior. This is a departure from existing methods (e.g. Dark Channel Prior, Color Attenuation Prior, DehazeNet etc.) that use patch based transmission estimation. The algorithm relies on the assumption that colors of a haze-free image are well approximated by a few hundred distinct colors, that form tight clusters in RGB space and pixels in a cluster are often non-local (spread in the whole images). The presence of haze will elongate the shape of each cluster to a line in color space as the pixels may be affected by different transmission coefficients due to their different distances to the camera. The lines, termed haze-line, is informative in estimating the transmission factors. In the algorithm, they first proposed a clustering method to group the pixels and each cluster becomes a haze-line. Then the maximum radius of each cluster is calculated and used to estimate the transmission. A final regulation step is performed to enforce the smoothness of the transmission map [2].

IV. Evaluation of Image Dehazing Methods

In previous sections, we have reviewed briefly five image dehazing methods. It is well-known that image dehazing is an ill-posed problem, which makes the evaluation of a candidate algorithm a very challenging work. The most usual way of evaluation is to visually observe different dehazing results by the user. However, it is time consuming and may result in different outcomes by users. Quantitative evaluation of dehazing is hence more preferable in practice. In supervised evaluation, the task is performed by measuring the similarity between the dehazing results and some ground truth images, which are provided by human observers. This has been widely used by researchers.

To quantitatively evaluate the dehazing results, we use three well-known indices: Mean Square Error (MSE) [7], Peak Signal to Noise Ratio (PSNR) [7], and Structural Similarity index (SSIM) [7].

Mean Square Error (MSE)

Mean Square Error of an estimator (of a procedure for estimating an unobserved quantity) measures the average of the squares of the errors or deviations—that is, the difference between the estimator and what is estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate. It is used to evaluate the change degree of the images. The smaller the value of MSE, the better the accuracy of the method. The formula, as follows:

$$\textbf{MSE} = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} (X(i,j) - Y(i,j))^2 \tag{11}$$

H and W represent the height and width of the image, respectively.

Peak Signal to Noise Ratio (PSNR)

Peak Signal to Noise Ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. PSNR is most commonly used to measure the quality of evaluating images. The signal in this case is the original data, and the noise is the error introduced by compression. Although a higher PSNR generally indicates that the evaluating images is of higher quality, in some cases it may not. Because the visual characteristics of the human eye are not taken into account, there is often a case where the evaluation result is inconsistent with the subjective feeling of the human being.

The PSNR (in dB) is defined as:

$$\textbf{PSNR} = 10 * log_{10}\left(\frac{(2^n-1)^2}{MSE}\right) \tag{12}$$

Structural Similarity index (SSIM)

The structural similarity (SSIM) index is a method for predicting the perceived quality of digital television and cinematic pictures, as well as other kinds of digital images and videos. SSIM is used for measuring the similarity between two images. The SSIM index is a full reference metric; in other words, the measurement or prediction of image quality is based on an initial uncompressed or distortion-free image as reference.

The SSIM index is calculated on various windows of an image. The measure between two windows x and y of common size $N \times N$ is:

$$\textbf{SSIM} = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{13}$$

with:
μ_x the average of x.
μ_y the average of y.
σ_y^2 the variance of x.
σ_x^2 the variance of y.
σ_{xy} the covariance of x and y.

The SSIM index satisfies the condition of symmetry: **SSIM**(x, y) = **SSIM**(y, x).

The structural similarity (SSIM) image quality assessment index is introduced to evaluate the ability to preserve the structural information of the algorithms. A high SSIM represents high similarity between the dehazed image and the ground truth image, while a low SSIM conveys the opposite meaning.

From the above introduction of the three indices, one should note that it is not possible to define a criterion for comparing dehazing that fits every problem optimally. For example, MSE and PSNR is based on examining the relationship between pairs of pixels. As a result, dehazing algorithms which are concerned with pairs can better use PSNR for evaluation. While for SSIM algorithms focus on preserving the structural information. A good dehazing will achieve large value of SSIM, and PSNR while small values of MSE.

V. Experiments on Image Dehazing

In this section, five well-known dehazing methods are selected for our experiments: Dark Channel Prior method [4], Color Attenuation Prior method [5], DehazeNet method [3], Single Image Dehazing via MSCNN method [6] and Non-Local Image Dehazing method [2]. The evaluation also shows the consistency of dehazing quality produced by them.

All the experiments were performed on the D-Hazy dataset [1], where all of the 50 clear images and 50 synthetic hazy images are used for our evaluation.

Particularly, for each image, we choose different evaluation of image dehazing methods. We can see that Dark Channel Prior and Non-Local Image Dehazing could get better dehazing results than others. Table I presents the quantitative measures of dehazing quality on all results produced by five dehazing methods. We see that Dark Channel Prior have the highest PSNR score above 62.066 and the lowest MSE score above 0.0523 and the highest SSIM score above 0.7920, which demonstrates it has best performance on image dehazing. When evaluating the relationship of pixel pairs, Dark Channel Prior has stronger ability to dehaze the given images than other methods. However, results by MSE, PSNR and SSIM show that Dark Channel Prior outperforms for producing more good dehazing, and Non-Local Image Dehazing and MSCNN have the bad performance. DehazeNet is generally satisfactory. As we all known, these indexes can not show the most realistic results and effects. We also need to evaluate the effects with human eye. Different methods have different results. In the figure 4, figures processed in different methods have better effects in MSCNN and Non-Local Image Dehazing.

Algorithms	MSE	PSNR	SSIM
Dark Channel Prior	0.052271	62.06592	0.791998
Color Attenuation Prior	0.059774	61.19266	0.765604
DehazeNet	0.057818	61.49813	0.788785
Single Image Dehazing via MSCNN	0.062187	61.01890	0.782033
Non-Local Image Dehazing	0.055244	61.18432	0.722483

TABLE I
MSE, PSNR, and SSIM scores on the total dehazing results by Dark Channel Prior method, Color Attenuation Prior method, DehazeNet method, Single Image Dehazing via MSCNN method, and Non-Local Image Dehazing method, respectively.

VI. Conclusion

In this paper, we use five well-known methods for image dehazing and three measures for evaluation of dehazing quality. The final evaluation results show that it is not easy to find a single quantitative measure for evaluating the dehazing quality, even with a group of ground truth given beforehand. Different datasets have different effects. To some extent, the evaluation criterion might vary in different applications.

Fig. 4. Some dehazing results on the D-Hazy dataset. From top to bottom: Hazy image, Ground-truth image and results obtained by Dark Channel Prior, Color Attenuation Prior, DehazeNet, Single Image Dehazing via MSCNN, and Non-Local Image Dehazing.

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