dehazing have their own advantages and disadvantages.

The thesis is organized as follows. In Chapter 1 we introduce the background. In Chapter 3 we introduce the dark channel prior and color attenuation prior in Chapter 4 we discuss image local features and enhancing saturation which basic work done in the early stage of this study. In Chapter 5 we study two important proposals of this study are CGAN application based on DCP and CNN deep learning application based on end to end. In Chapter 6 we introduce the software works tools and conclude in Chapter 7.

2. Two Typical Prior Algorithms and Limitations

2.1. Prior Theory

Prior to the emergence of prior algorithm, scientists were studying the image dehazing technology, mostly by means of 3D reconstruction and object recognition. People have not found a simple and effective way to achieve this goal before. Prior technology is a very simple, even surprising statistical law of effective dehazing method. Different from the previous methods, they focused on the statistical characteristics of haze-free images. The rule is found through statistics, that is to say, in a haze-free image, every local area is likely to have shadows, or things of pure color, or things of black. Therefore, it is very likely that at least one channel in each local area will have a very low value. They call this statistical law the dark channel prior. Intuitively, dark channel prior believes that there are always some dark things in every local area. This rule is very simple, but it is the essential basic rule in their study of demisting.

Because the haze is always gray, once the image is affected by the haze, these things that should be very dark will become gray. Not only that, according to the physics formula of haze formation, researchers can also judge the haze concentration according to the gray degree of these things. Therefore, the dark channel prior proposed by them can effectively remove the influence of haze and estimate the distance of objects by using the concentration of objects.

2.1.1. Hazy image formation model

The hazy image degradation model consists of two parts: the scene reflection light attenuation model and the atmospheric light imaging model, which is proposed by McCartneyin [58]. Nayar and Narasimhan [59][60], further derive the model later, and the mathematical models used to describe the above processes are (2-1) and (2-2) as follows:

$$I(x)=J(x)t(x)+A(1-t(x)) \tag{2-1}$$

Among them: I (x) is the light intensity received by the observation point, J (x) is the light intensity radiated by the scene point, that is, the haze-less image to be restored, t (x) is the light transmission map, J (x) t (x) is the scene reflection (or emission) light attenuation model, A (1-t (x)) is the atmospheric light value, and A (1-t (x)) is the atmospheric light imaging model.

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

The d(x) in the formula is the distance between the observation point and the scene point, the atmospheric light scattering coefficient is beta, and the beta is regarded as a constant in the visible light range.

2.1.2. Ill-posed problem

Among the restoration methods, the commonly used physical model is the atmospheric scattering model proposed by Narasimhan et al. (1), which is an undesirable problem. That is to say, there are two unknown variables in the same formula, that can't be solved by the traditional method and need to be solved by regularization. Using this model, only the transmittance value of each point in the image and atmospheric light can be determined to get a better restoration result [61][62][63]. However, it is not easy to determine the transmittance and atmospheric light. Narasimhan et al. use two gray-scale images under different weather conditions to extract the scene depth [64]. Okaley's group use photoelectric devices to obtain the scene depth, so as to determine the transmittance function [65]. These methods can't be used in practice because of the limited conditions.

The principle of DCP belong to a color image J (x) with R, G and B channels, two minimum filters are performed on R, G and B channels and filter template Omega (x) of N × N size. Normally, N is set to 15, through statistics of a large number of outdoor haze-less image, it is concluded that the dark channel of outdoor haze-less image has properties. Our goal is to turn the ill-posed problem into the well-posed problem. So, the solution is present, and solve the problem, then Parament is accompanied by the solution of the chemicalization.

2.1.3. Algorithm

The haze removal algorithm based on dark channel prior is as follows: 1) The R, G and B channels on both sides of the equation (1) are divided by the atmospheric light value A at the same time.

$$\sum_x \| \nabla I(x) \| = t\sum_x \| \nabla j(x) \| < \sum_x \| \nabla J(x) \| \qquad (2\text{-}3)$$

2) To get atmospheric light value A: Select the brightest 0.1% pixels in the dark channel image of I(x), where the haze is thickest, and then correspond these points to the same position of the original image I(x). In these points of the original image I(x), select the maximum value of three channels as atmospheric light value respectively. Ray propagation map is t(x): Calculates dark channels on both sides of the equation at the same time.

$$J^{dark}(x) = \min_{x\in\{r,g,b\}}(\min_{y\in\Omega(x)}(J^c(y))) \tag{2-4}$$

According to the dark channel prior theory,

$$\min_{y\in\Omega(x)}(I^c(y)) = \tilde{t}(x)\min_{y\in\Omega(x)}(J^c(y)) + (1-\tilde{t}(x))A^c \tag{2-5}$$

So, the following formula can be obtained,

$$\min_c(\min_{y\in\Omega(x)}(\frac{I^c(y)}{A^c})) = \tilde{t}(\mathrm{x})\min_c\left(\min_{y\in\Omega(x)}\left(\frac{J^c(y)}{A^c}\right)\right) + (1-\tilde{t}(\mathrm{x})) \tag{2-6}$$

4) In order to obtain the image until the visual authenticity effect, a coefficient is multiplied in the calculation of the ray transmission map.

In order to remove the halo phenomenon, soft matting is needed for the optical transmission graph t (x), which is usually guided by filtering [66].

5）Restoring haze-less image: using formulas,

$$J^{dark}(x) = \min_c(\min_{y\in\Omega(x)}(J^c(y))) = 0 \tag{2-7}$$

Haze-less image were restored in three channels. Aiming at the problems of dark channel prior dehazing method, the overestimated atmospheric light is self-adaptively corrected to detect and optimize unreliable transmittance estimation in order to obtain better dehazing effect for the image. Dark channel prior dehazing effect generally has high contrast and color saturation, but there are some visual defects such as halo and block effect [67]. This is due to the disproportionate relationship between partial transmittance and depth information. For this part of the unreliable transmittance estimation, soft matting and directed filtering are usually used to refine the operation based on filtering, so that the edge information of the transmittance map is closer to the original image. However, the refinement operation based on filtering has the defect that the transmittance does not conform to the variation rule of depth information, so that the estimation deviates and the contrast of haze-less image is weakened.

With the dark channel prior(DCP) algorithm, it is possible to achieve the ideal implementation of dehaze treatment, but also occurred in the bright area of the miss repair, as shown in the following figure: Figure c is right figure(a) local magnification, and Figure d is figure(b) local magnification.

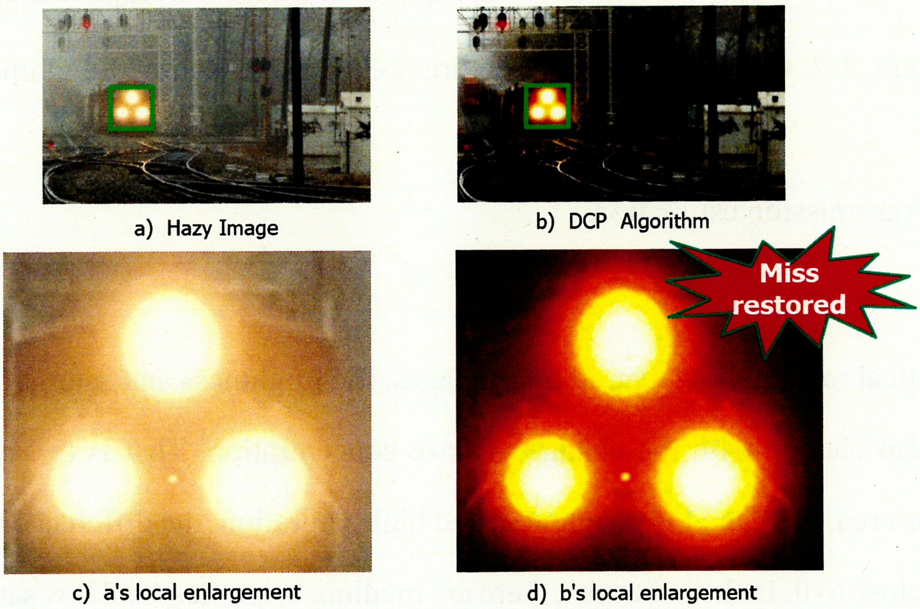


Figure. 2-1. Miss repair image

2.2. Color Attenuation Prior

Different from dark channel prior, this was a new prior theory at that time, that is, the prior of color attenuation. By modeling the scene depth of the hazy image, that is to say, building a linear model, the researchers study the linear relationship between the depth, brightness and saturation of the image [68].

Create a model of scene depth and to dehaze, but express color attenuation overall, then it doesn't look very good.

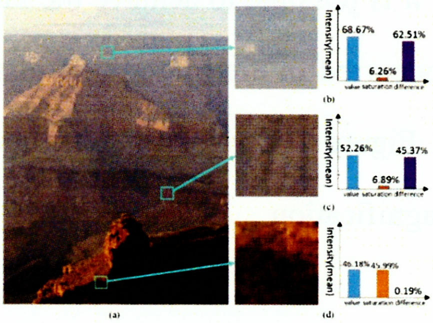
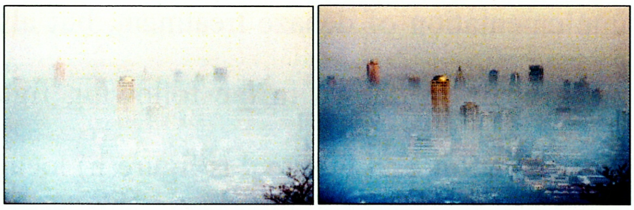


Figure. 2-2. CAP image



a) Input haze image b) Input haze image

Figure. 2-3. Comparison with I/O image

2.2.1. Transmission estimation

Statistical results show that, in hazy images, the brightness and saturation of the pixels also change with the change of haze concentration. That is to say, in the haze-less area, there are low brightness and high saturation, the difference between them is close to 0. In the haze area, there are medium brightness and low saturation, the difference between the two is relatively large. In the haze area, there are high brightness and very low saturation, the difference between the two is very large. It can be seen that with the increase of haze concentration, the brightness gradually increases while the saturation gradually decreases. In other words, the haze concentration is proportional to the difference of gray level and saturation of the pixels. Therefore, the difference between brightness and saturation is used to estimate the hazy concentration of haze map.

$$\mathrm{d(x)} \propto \mathrm{c(x)} \propto \mathrm{v(x)} - \mathrm{s(x)} \tag{2-8}$$

This is HSV (Hue, Saturation, Value) model. In general, haze concentration increases with the change of scene depth, where d(x) is depth of field and c(x) is concentration of haze. v(x) is value of brightness of scene, s(x) saturation. This formula is color attenuation prior.

Consider this statistic as a prior color decay. With the increase of depth, the increase of V value and saturation decrease the increases. In other words, angle alpha is positively correlated with depth.

2.2.2. Linear model

According to the following linear model, the scene depth can be predicted with brightness and saturation as variables, and inference can be made. Formula as follow,

$$\mathrm{d(x)} = \theta_0 + \theta_1 v(x) + \theta_2 s(x) + \varepsilon(x) \tag{2-9}$$

Among them, x is the position in the image, D is the field depth, V is the brightness component of the blurred image, s is the saturation component, theta 0, theta 1, theta 2 are unknown linear coefficients. Theta 1, theta 2, theta 3 are unknown linear parameters, ε(x) is the sum of random errors of the model represented by random variables, and E can be regarded as a random image, that is, a random image.

In the final formula, if the mean value is 0, the standard deviation is Gauss distribution. And we assume that the X is very small, close to zero.

The Gradient of (2-2)

$$\nabla \mathrm{d} = \theta_1 \nabla v + \theta_2 \nabla s + \nabla \varepsilon \qquad (2\text{-}10)$$

Using 6^2 instead of ε(x), According to the Gauss distribution, the following formula can be obtained.

$$\mathrm{d(x)} \sim \mathrm{p}(\mathrm{d(x)}|\mathrm{x}, \theta_0, \theta_1, \theta_2, \sigma^2) = \mathrm{N}(\theta_0 + \theta_1 \mathrm{v} + \theta_2 \mathrm{s}, \sigma^2) \qquad (2\text{-}11)$$

Experiments show that the edges of the original image are basically similar to those of the depth map obtained, so we can use (2-11) to express the depth of field.

Then, the values of theta 1, theta 2, theta 3 are trained by machine learning algorithm.

Estimation of Atmospheric Value A: Assume that when the distance is wireless, I = D. Select the brightest value of 0.1% pixel. The formula for scene restoration is as follows:

$$\mathrm{J}(x) = \frac{I(x)-A}{t(x)} + A = \frac{I(x)-A}{e^{-\beta d(x)}} + A \qquad (2\text{-}12)$$

In order to remove noise, the value of t(x) is 0.1-0.9.

$$J(x)=\begin{cases}\dfrac{I(x)-A}{0.1}+A,t(x)\in[0,0.1)\\ \dfrac{I(x)-A}{t(x)}+a,t(x)\in[0.1,0.9]\\ \dfrac{I(x)-A}{0.9}+A,t(x)\in(0.9,1]\end{cases} \tag{2-13}$$

2.2.3. Training

Depth maps are obtained through simple supervisory training. As the training data, more than 150 hazy images were collected. Finally, the appropriate parameters were obtained. The training sample consists of a blurred image and its corresponding ground truth depth map. In order to find the solution of the difference between the scene depth d (x) estimated by the minimization formula (4) and the true depth, the Zhu team minimized the loss square function.

In the actual operation process, the white object in the remote image has the characteristics of high brightness and low saturation. The trained model will mistake the white object as the distance from the actual distance. At this time, it is necessary to set up a small window to deal with the minimum operation, as follows: d(y) is a depth map trained.

$$d_r(x) = \min_{y\in\Omega_r(x)} d(y) \tag{2-14}$$

$$\mathrm{J}(x) = \frac{I(x)-A}{min\{max\{e^{-\beta d(x)},0.1\},0.9\}} + A \tag{2-15}$$

2.3. Problem Points

2.3.1. The defects of prior theory

In recent years, researchers have proposed many prior hypotheses to obtain some statistical or decisive properties of haze maps.

A prior dehazing algorithm has achieved good results on some haze maps. These algorithms require haze maps to fully conform to scenario assumptions. Although a prior dehazing algorithm achieves dehazing, this kind of algorithm has the disadvantage of weak applicability. In the real world, many haze maps do not always conform to the hypothesis, so the results of haze removal of these algorithms will have a variety of problems. Several typical cases are as follows. For example, Fattal's algorithm is suitable for haze with light haze, but it is prone to noise in haze with heavy haze. Because of its rich color information and the need for color difference between pixels, these requirements are not available in haze maps. K.He's algorithm is not suitable for sky or bright scenes, because K.He's method assumes that atmospheric light intensity is brighter than all pixels [69]. However, in a picture with a bright sky or light source, there will be some brighter points than the light. K.He's method estimates the transmittance of these pixels very small, even some negative numbers. In fact, the normal range of transmittance should be between 0 and 1. After the final restoration, the color difference appears in the sky region of the image. Berman's method is not suitable for images whose light intensity is obviously brighter than other pixels.

In summary, prior dehazing algorithms are applicable to some haze maps with specific properties, but not very general. Therefore, with the development of machine learning, data-driven dehazing algorithm has become popular and achieved better results than prior dehazing algorithm. With the expansion of AI application, the research of data-driven dehazing algorithm has gradually increased, and some achievements have been achieved.

The core of data-driven model is training set. Using the optimal training set can greatly improve the performance of the model. However, there is some research on training set processing in these algorithms. In addition, the accuracy of many data-driven models is not higher, then the regression error is large, resulting in some bad results of haze removal.

2.3.2. The disadvantage of deep learning

CNN is a machine learning model under deep supervised learning. It can mine local features of data, extract global training features and classify them. Its weight-sharing structure network makes it more similar to biological neural network and has been successfully applied in various fields of pattern recognition. CNN combines local perception regions of face image space. Sharing weights and down sampling in space or time can make full use of the local characteristics of data itself, optimize the model structure and ensure certain displacement invariance [70].

Gibson synthesized hazy images from depth images [71], so that the true depth of the synthesized hazy images can be known. Then the real depth values are used as learning labels to train the data-driven model, and then the transmittance of the tested images is obtained through this model for hazing removal. Huang used a local linear model to learn the relationship between the haze-less map and the corresponding transmittance map [72]. Tang first defines some haze-related features, and then uses stochastic forest regression to establish the mapping between feature vectors and transmittance. By inputting the test haze map, the corresponding transmittance map can be obtained based on the trained data-driven framework. Finally, the corresponding dehazing results can be obtained through the physical formula of the haze map. In addition, there are also deep network dehazing methods. These methods use convolutional neural network to learn accurate depth information, and is can deal with various complex scenes in haze maps. Cai and others propose a trainable end-to-end CNN [73][74], which can obtain estimates of transmittance maps. Ren's method introduces a multi-scale CNN network for dehazing [75], this method uses a rough scale network to learn the structure information of transmittance, and then uses an optimized scale network to optimize the transmittance map.

These data-driven dehazing algorithms do not deal with the training set. The training set is fixed and not fully adapted to the data-driven model. In addition, the accuracy of many models is not high, and the regression error is large. For different types of test haze maps, the transmittance will be underestimated or overestimated, leading to incomplete or excessive haze removal.

2.3.3. Our research processes

As mentioned above, with the help of in deep learning, this study carries out research from two perspectives of model accuracy and training set search. In order to reduce the model error, a two-level joint Gauss process regression model is proposed. From the perspective of data set selection, the data-driven model is optimized, and the data-driven model used in the dehazing algorithm is specifically designed.

This chapter introduces the success and shortcomings of traditional dehazing methods, especially DCP methods. In particular, the plan improvement strategy and future work are put forward.

3. Preliminary Research Work

3.1. Image Local Features

3.1.1. Experiments

Based on the research results of his term, the usage of Soft Matting has not been described in detail yet. Using the local gradient key point extraction technique, it consists of two stages, detection of key point detection and description of key point amount. Each process is as follows, i. Scale and key point detection, ii. Localization of key points, iii. Calculation of orientation, iv. Description of key point amount. Then i. In scaling and key point extraction, scale and key points are detected by DoG processing, and in ii. localization of key points, points not pointed as key point points are deleted from the key points detected in 1, Perform pixel estimation. iii. In the calculation of the orientation, obtain the orientation of the key point in order to obtain the invariant key points for the rotation. iv. In the description of the key point amount, in iii, describe the key point amount of the key point based on the obtained orientation. Details of each process will be described below.

Dark channel processing is based on the observation of the outdoor haze-less image of K.He et al [7]. In most of the image areas other than the sky, at least one of the color channels has very low intensity in some pixels.

In the case where the image has few texture patterns or the light from the object is blocked by dark channel, it is difficult to see the difference only with the dispersion maximum map creation process, and select an image with noises that is possible of doing it. Therefore, when the variance value of the color image patch falls below a certain threshold value, an image that takes the maximum value in transmission is selected. This is because there is a high possibility that good results are obtained because direct light J from the object becomes large where transmission value is high.

For the dispersion maximum map creation process and the transmission maximum map creation process, a haze removal effect can be expected in the case where there is unevenness even by single process alone. However, there is a possibility of selecting an image including noise only by the dispersion maximum map creation processing. When the haze becomes dark by only the transmission maximum value calculation processing, a dark portion in the image is found, and it is possible to situate which dehazing processing using the dark channel priors difficult to be established. Therefore, by looking at the threshold value of the dispersion value, it is selected whether to use the dispersion maximum map or the transmission maximum map and combines these two processes to create an integrated image (Figure. 3-1).

1(a) 1(b)

2(a) 2(b)

Figure. 3-1. Hazy image (a) and dehazing image (b)

3.1.2. Related works

In our research, we proposed a method to remove haze from uneven dehazing image with haze density change, using dark channel prior and local gradient key point extraction technology. Conventional haze removal is based on the assumption that the haze is uniform in the space, and it was not able to cope with the state with the concentration change. In the proposed method, the dispersion and transmission are combined using the color image, and images with less haze shading are connected well, and the image visibility is improved as a whole. As a result, it was possible to remove haze with shading which was difficult to take with only one piece. Estimate the transmission map by using the image local information and shaping the coarse map using the detailed map. In this way, a clear image is obtained while maintaining the haze removing quality.

3.1.3. Conclusion

We have proposed a fast algorithm to solve the matting Laplacian matrix. Our algorithm is faster when the kernel is larger, and the matrix is less sparse. which is against conventional theories.

Our algorithm is non-approximate with a given kernel size r. It provides us a chance to observe the results of larger kernels, which are almost unavailable in previous methods. The result of a large kernel (e.g., $r > 1$) is different with the one of the small kernels (e.g., $r = 1$), but is not necessarily degraded. In our alpha matting paper, we have found that an appropriately large kernel actually improves the quality.

Although our algorithm is particularly designed for the matting Laplacian matrix, a similar idea is expected to work in some other matrices used in computer vision/graphics problems. The focus is to reduce the running time in the matrix multiplication step (Lp) and to achieve speed-up by faster convergence.

The matrix-vector multiplication is 2D image filtering. So, the O(n) time computation of Lp is actually a fast filtering algorithm. Inspired by this concept, we propose a novel filter called guided filter [58]. It is not only fast but also has very good quality, as we shall discuss below.

3.2. Enhancing Saturation

3.2.1. Algorithm

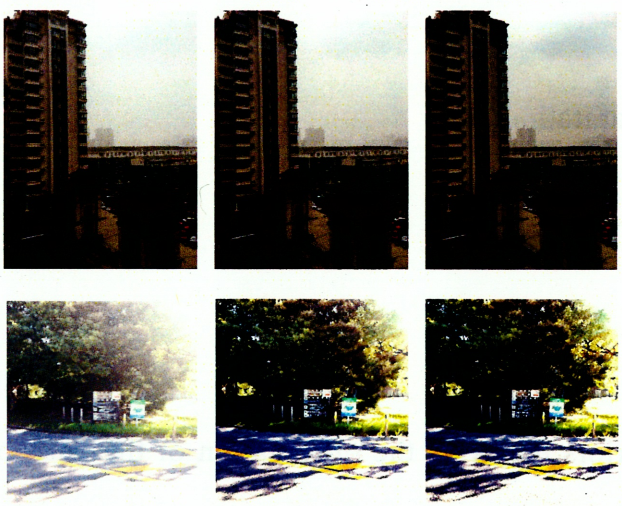
Dark channel priors based on the observation of the outdoor dehaze image of K.He's group. In most of the image areas other than the sky, in RGB channels model, at least one the color channels have the lowest intensity in some pixels.

The dark channel calculation, the brightness histogram is calculated. Based on the transmittance and the estimated atmospheric light component, a restored image. (formula 3-1)

$J^{dark}(x)$ haze removal picture the center (x) or the price of the dark channel which corresponds to picture element x. The strength of one optional channel value over R, G and the B channel. $J^{c}(y)$ is the picture element, and y is the local territory Ω(x). Min is the mix function which finds the-minimum value. In the case where the image has few texture patterns or the light from the object is blocked by dark haze, and it is possible that the situation that dehazing processing using the dark channel model is difficult to be established is possible.

A hazing algorithm for color space. Based on the characteristics of the maximum saturation of the no hazy image without haze before and after the hazing, the linear dehazing model meets the characteristics of the haze, then the parameters are determined.

We compare the dehaze image as follow (Figure 3-2):



(a) (b) (c)

Figure. 3-2. Haze removal using a single image.

(a) Haze image. (b) Conventional proposal. (c) Step proposal.

3.2.2. Experiments and applications

In order to verify the effectiveness of the proposed dehaze method, we validated it on various hazy images and compare with old methods.

MSE represents the mean square error of image I and Image J, and $M_K \times N_K$ is the figure. The lowest value, the best quality.

$$MSE(X,Y) = \frac{1}{H\times W}\sum_{i=1}^{H}\sum_{j=1}^{W}(X(i,j) - Y(i,j)) \tag{3-1}$$

Then using MSE, the definition of solving PSNR is as the formula 3-2, then it can get it, as follow,

$$PSNR(X,Y) = 10\lg\left(\frac{MAX^2}{MSE}\right) \tag{3-2}$$

About of the hazy image using conventional proposal. The flat which applied a proposal is that case. PSNR are indicated in table 3-1. But, MSE prepared a correct answer picture and compares each picture element respectively in the formula 3-2. The size by which m, n is the length and the width of the picture at this time. X' a former picture and X' indicate a degradation picture. When PSNR will be made the formula later, it'll be as follows.

MAX is the biggest picture element value a former picture can take. In this way, a clear image is obtained while maintaining the haze removing quality.

Table 3-1 The value of the test outcome

Contents	Mean squared error	
	Mean squared error	Peak single to noise ratio[dB]
Haze image(a)	8917.39	4.68
Conventional proposal(b)	4989.76	15.43
Step proposal(c)	2898.56	20.18

For analysis image quality evaluation parameters, we decrease the MSE, increase PSNR and be improved can confirm that a result of each of conventional method and suggestion proposal is compared more than table 3-1.

3.2.3. Conclusion and discussion

this research, we proposed a method to remove haze from uneven dehaze image with haze density change, using dark channel model and enhancing saturation extraction technology.

So, the outdoor hazy images in the environment that haze occurred is assumed by our research, and the information can put as well as image processing using still information are also used. It's done and improvement of the visibility was Realized. Improvement of visibility for a hazy outdoor surveillance single color image and promoted visibility improvement.

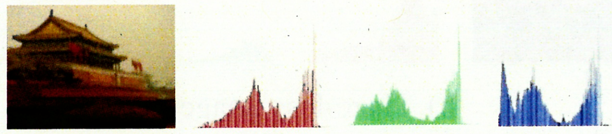
3.3. RGB Value

3.3.1. Related works

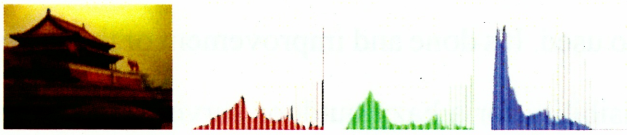
In order to obtain the three-channel values in different processing stages, the following three types of images are specially investigated: the original input hazy image, the haze-less image and the output image after hazing removal. In the following figure, they are represented by 1 (Haze), 2 (Haze-less) and 3 (Dehaze), respectively. The R, G and B histograms of the three channels of these three types of images are obtained.

The histograms of the RGB channels of the three pictures are as follows:

a) Haze image

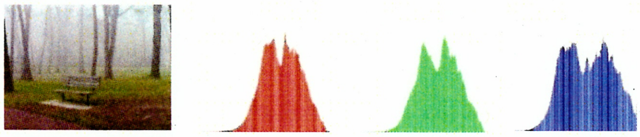


b) Haze-less image

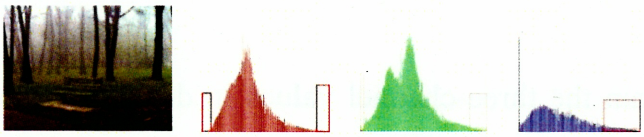


c) Dehaze image

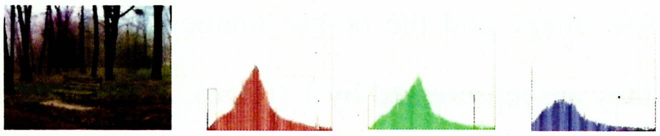
Figure. 3-3. Tian'anmen image before and after dehazing and its RGB values



d) Haze image

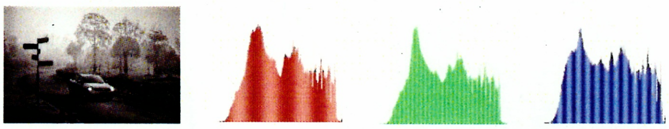


e) Haze-less image

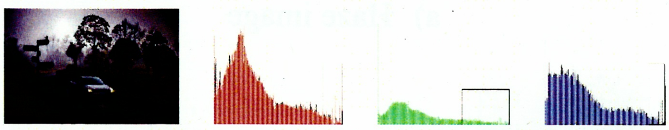


f) Dehaze image

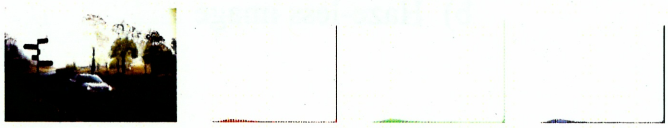
Figure. 3-4. Trees image before and after dehazing and its RGB values



g) Haze image



h) Haze-less image



i) Dehaze image

Figure. 3-5. Car image before and after dehazing and its RGB values

3.3.2. Experiments

As mentioned above, the three channel R, G and B values of three types of images are obtained. Next, the relationship between the R, G and B values and the parameters calculation in the physical model of hazy images is studied in depth.

3.3.3. Discussion

Comparing R, G and B histograms of hazy images and haze-less image, we find that at least one of the three channels are very similar. Based on this empirical value distribution, this thesis explores and studies new breakers in dehazing.

4. GAN Utilization based on Dark Channel Prior

4.1. Background

K.He's dark channel prior algorithm [7], there is a problem of improper handling of the highlighted position in the haze removal, so we propose the DbGAN (dark channel prior based of GAN) network algorithm, then designed the generator and discriminator. After DCP restoration, the RGB value of the image processing bug containing the highlighted area is used as the input, then compared with the RGB information of the haze-less image, so as to generate the training. At the same time, the target setting technique was adopted, and it was generated the processing Image RGB finally, it can achieve the effect of removing haze in the highlighted area from restoration, then make up for the shortcomings of the DCP algorithm.

4.2. Generator and Discriminator

In the industry, there are representative DCP algorithms to dehaze image, but there is a problem of haze removal highlight area. Therefore, this study proposes DbGAN deconvolutional networks learning algorithm, designs generator and discriminator, after DCP restoration, RGB value of image processing bug with highlight area is used as input content, compared with RGB information of haze-free image images, and generated simultaneously, the method of discriminating and setting target map is used to generate RGB processing map. After restoration, the effect of dehazing in the highlighted area is well-recognized, which makes up for the shortcomings of DCP algorithm [76].

In order to avoid secondary dehazing and disadvantages, DhNet is proposed to carry out haze removal from end to end. Based on the deep convolutional neural network, learning hazy image directly from the data, in order to increase the depth or breadth of the network, compared with other commonly used strategies, using dilated convolution to increase the field of vision of image processing, and using CNN to improve noise reduction. The noise removal rate in hazy image is greatly improved, and the calculation speed is greatly accelerated after network training.

4.2.1. Generator

The design idea of this study is based on the dark channel prior, adding anti-training, improving the bright part distortion of DCP algorithm. In this work, it is called DbGAN. Its advantage is that the data flow of this algorithm can be traced, the third-party links are few, and the data reliability is high. In fact, the basic idea of GAN is not complicated. The core of GAN is composed of two neural networks that conflict with each other. These two networks will "cheat" each other with more and more complex methods. This situation can be understood as the minimax game tree in game theory. For this reason, we need to introduce two concepts, generator and discriminator. The functions of these two designs are described below.

The generator uses a convolution encoder as the generator model, the encoder uses the image used to removal the highlighted area as the input, generates the potential feature representation of the image through convolution operation. The