2017 International Conference on Computer Network, Electronic and Automation (ICCNEA 2017)

Single Image Dehazing Based on Deep Neural Network

Dewei Huang, Kexin Chen
College of Electronic Engineering, South China Agricultural University, Guangzhou, China
E-mail: huangdewei@stu.scau.edu.cn; 285078375@qq.com

Jianqiang Lu
College of Electronic Engineering, South China Agricultural University, China;
Guangdong Engineering Research Center for Monitoring Agricultural Information, China;
Science and Technology Program of Guangzhou, Chian.
E-mail: Ljq@scau.edu.cn

Weixing Wang
College of Electronic Engineering, South China Agricultural University, China;
Guangdong Engineering Research Center for Monitoring Agricultural Information, China;
Science and Technology Program of Guangzhou, Chian.
Corresponding author
E-mail: weixing@scau.edu.cn

***Abstruct*—This paper proposes a single image dehazing based on deep neural network that is to deal with haze image. In this paper, we build up a deep neural network to restore the hazy image.We test our method both objective and subjective and compare with classical method for dehazing. Our test shows that our method works better than the others in reducing Halo effect and also our method does well in restore colorful of input image. Finally, our method process faster.**

Keyword-Dehazing; Deep neural network; Imagedepth map

I. INTRODUCTION

Outdoor images taken in bad weather usually had loses contrast and becomes blur which is resulting from the fact that light is absorbed and scattered by the turbid medium such as particles and water droplets in the atmosphere during the process of propagation [1]. These hazy image become useless in detection or finding some interesting information. Using dehazig method can restore the hazy image and get more detail so that more interesting information shows in the restored image. It does make sense to do research in image dehazing.

Image dehazing can be divvied into two kinds that one is based on traditional image processing method such as the enhancement of histogram[2,3], and Retinex[4]. However, this kind doesn't care about how the haze comes so that the result always loses a lot of information or cannot remove haze clearly. And the other kind is based on atmospheric scattering model that concerned about how the haze occurs in the image and then estimate the parameters for the model to dehazing. Tan [5] maximum the local contrast of the image based on Markov Random Field (MRF) to gain clear image, but the image is always over-saturated. Fattal[6] is based on Independent Component Analysis to remove haze, but they failed while the haze is dense. With a large number set of statics, He et al. [7,8] propose dark channel prior (DCP) that in the non-sky area, at least one color channel has some pixels whose intensities are very low and trend to zero. They make a big progress in haze removal because this approach is simple and effective. However, they may fail when image has large area of sky or white scene. Guided filtering is proposed[9,10] to improve the dark channel later. Tarel et al.[11] make an approach which is based on the median filter, but this approach cannot handle the edge of the image. Zhu et al.[12] assume that the relationship between transmission and brightness and contrast is linear, but this model is not so clear.

In this paper, we propose a new method to dehazing that based on deep neural network. We using a lot of clear image and its real depth map the feed our network so that it can describe the relationship between input image and its depth map correctly. As the result, our dehzing result becomes better and faster.

II. DEHAZING METHOD

A. Atmospheric Scattering Model

Atmospheric scattering model [13] is wildly used in dehazing and it can be described as quation (1)(2) shown:

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

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

Where I(x) is input image with haze; J(x) is output image what we wanted; t(x) is transmission map; A is global air light; d(x) is depth map; β is coefficient which can be described as constant. There are three unknown variables in equation so that we cannot solve the model unless we estimate transmission map and global air light. In this paper, we try to estimate transmission map from depth map, and estimate the rest coefficient for our dehazing method.

From equation (1)(2), we know that depth map play an import role in dehazing method. Narasimhan [14]points that β can be described as constant in the same environment so we can try to estimate transmission map by depth map. From discussion above, we can restore hazy image if we know depth map and air light.

B.Depth Map Estimating Based on Deep Neural Network

We can use two deep neural network to estimate depth map based on Davied Eigen' work. One is to estimate raw depth map and the other is to refine it. The structure of our neural network is shown in Fig.1. We do some improvement based on Davied's work.

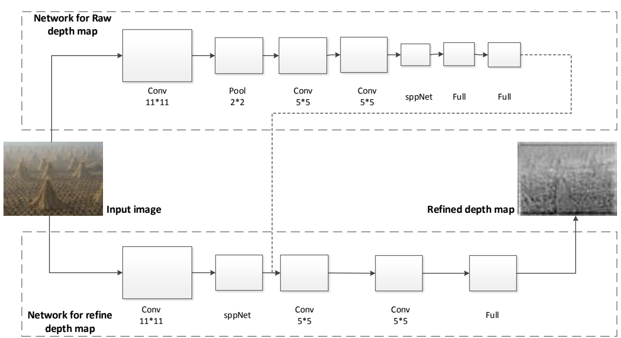


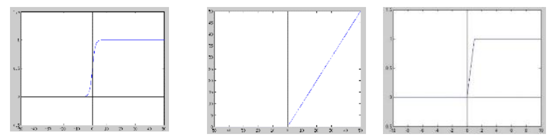
Figure 1. The network for getting depth map

As shown in Fig.1. we firstly build up a deep neural network to estimate raw depth map and it consist of seven layers. Input image is sent to first convolutional layers and then do max pooling for it. We do out the result to two convolutional layers later. In order to fit any size of the input image, we do spatial pyramid pooling (SPP)net for the result and the do two times of fully connect.

We ever try to use raw depth map to restore hazy image, but it does a bad work. We should build up another network to refine the raw depth map.Our refine network is shown in Fig.1. We firstly feed input image in convolutional layers and SPP net to fit the output size of the raw depth map. This result and the raw depth map as input for rest layers. We feed them in a convolutional layers and fully connection layers so that to refine the depth map.

C.Training Details

The last layer is need linear regression so we use linear active function at the last layers. However, active function of the other layer should do some preprocess. In the programming, always make transformation for the input image so that all of the value is between 0 and 1. From discussion above, it seems that Sigmoid function is a good choice, but it will easily cause gradient disappearance; Reluhas good performance is positive axis and has sparsity in negative axis. Based on analysis above, we cut down the RuLu while the input is larger than 1. Sigmoid ,ReLu and our active function is shown in Fig.2.



a. Sigmoid b. ReLu c. Ours

Figure 2. Active function

Our loss function is as equation (3), it is a scale-invariant loss function that is proposed by [15].

$$D(y, y^*) = \frac{1}{2n}\sum_{i=1}^{n}(\log y_i - \log y_i^* + \alpha(y, y^*))^2 \tag{3}$$

Where y and y^* respectively are training data and its predicted data and in our paper it mean the real depth map and the predict depth map. The $\alpha(y, y^*)$ is described as equation(4)

$$\alpha(y, y^*) = \frac{1}{n}\sum_i(\log y_i^* - \log y_i) \tag{4}$$

We build up the loss function what we required and it is shown in equation (5)

$$L(y, y^*) = \frac{1}{n}\sum_i D_i^2 - \frac{\lambda}{n^2}(\sum_i D_i)^2 \tag{5}$$

Where λ is set to 0.5.

D. Estimate Air Light

We try to reformat the equation (1) and it is shown as equation (6):

$$J(x) = \frac{I(x) - A}{t(x)} + A \tag{6}$$

We has estimated transmission map and now need to estimate the air light. Air light can be consider as constant in the same environment, such Ancuti compare the input image and its semi-inverse image in CIE color space and marke some special point and then chose the brightest as air light; He et al. mark the top brightest 0.1% in the dark channel and then pick the brightest in input image. Another researcher consider the air light is not constant in the same environment, such Yang Xun using linear interpolation to estimate air light in the direction of attenuation of illumination.

We do preprocess to the input image so that the estimate value of air light would be exactly. In this paper, we consider air light is a constant and that can get from the input image. In the image the white color is getting close to 1 and if we chose the brightest pixel directly from input image, we can almost get a very value that closed 1. We first set a threshold to remove the high value and the get the ighest value in the processed image. The step of our method is shown in Fig.3, we remove the value which is higher than the threshold in each R, G, B channel and then combine them. After does this preprocessing, the top highest value would be removed. We chose top 0.1% highest value from processed image and compute the average as air light.

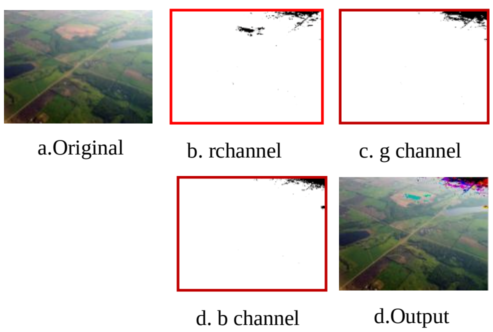


Figure 3. Estimate air light

III. Experimental Result and Analysis

A. Prepare Training Data

In this paper, we use natural hazy image and some synthetic image to train our model and as the result our method can get more suitable for dehazing. Expending the training data can lead our method has more generalization ability. The natural image, we get from the open source and token image by ourselves.

Synthetic hazy image can consider as the inverse processing of dehzing, so we need clear image and its depth map to estimate hazy image. Saxena et al. has built up a large database that include a large number of clear image and its real depth map. The database is wildly used in researching. They use professional device to get the depth map so that it is exactly precision and also this database is suitable in synthetic hazy image. The step to synthetic hazy image is shown in Fig.4.

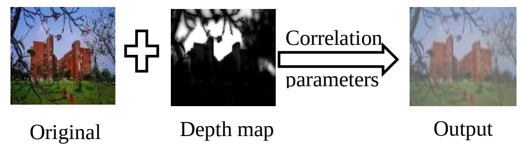


Figure 4. Synthetic hazy image

From equation (1), we know that when $I(x) = A, t \to 0$. It means that air light is very close to the pixel value when transmission value is very small and close to 0. As the result, we can chose the value as air light where the depth value is highest.

B. Experimental Result

Using the model that we have trained before to estimate depth map and air light and then put them into equation (6) to get clear image. We compare with He's method and Tarel's method objectively and subjectively. Our test environment is in Ubuntu 14.04 operating system with Intel Xeon(R) CPU E5-2620 v4 @ 2.10GHz ×16 and GTX TIAN X. We use Tensorflow and Matlab2014Ra to do simulation.

C. Qualitative Analysis

Having done a large number of test, wo select three of them to shown in this paper. Fig.5, 6 and 7 is our test result with Tarel's method, He' method and our method. It is obvious that all of them do efficiency in dehazing. Our statistics shows that Tarel's method cannot remove the hazy thoroughly and it seems some haze remain in the output image; He's image do better than Tarel's method but it fail in color restoration. The output image will be dark in He' method. Our method does better than the other method subjectively. Our method perform better in haze removal and color restoration and also our method can show more details in the output image.

Figure 5.a: Input image; b: He's method; c: Tarel's approach; d: ours

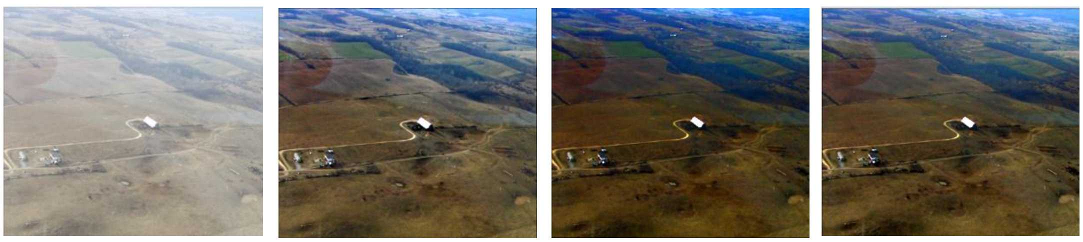


Figure6.a: Input image; b: dark channel; c: Tarel's approach; d: ours

a. Original b. Tare's c. He's d. Ours

Figure 7.a: Input image; b: dark channel; c: Tarel's approach; d: ours

D. Quantitative Analysis

Firstly, we use MSE assessment to compare the three method in this paper, and the MSE is as equation (7) shown.

$$MSE=\frac{\sum_{0?i<M}\sum_{0?j<N}(f_{ij}-f_{ij}^{'})^2}{M\times N} \qquad (7)$$

where f_{ij} is input image, $f_{ij}^{'}$ is the output image, M and N is the numbers of x and y axis. The smaller of this value, the better of the output image.

We also use Hu Zi'ang's[16] assessment to evaluate the methods and this assessment is shown in equation (8)

$$Q=\frac{S\times Hist}{e^{-L}} \qquad (8)$$

Where $Hist$ is histogram similarity function and when $Hist$ is closed to 1, it is better.; L is edge intensity function which is using Canny to gain and the bigger of L ,the better; S structure similarity function; the bigger of Q the better ntegratedly. We the get two table is shown in Table Iand II for Fig.5, 6, 7.

TABLE I. MSE FOR EACH METHOD

Test image	Tarel'	He's	Ours
Fig 5.	0.412 6	0.250 9	0.102 2
Fig 6.	0.618 6	0.471 0	0.149 4
Fig 7.	0.109 1	0.095 8	0.100 5

TABLE II. COMPREHENSIVE EVALUATION

Test image	Tarel's	He's	Ours
Fig 5.	0.455 7	0.674 9	1.028 9
Fig 6.	0.237 0	0.349 6	1.005 3
Fig 7.	2.541 0	1.941 6	1.476 3

From table I, it is easily to find that Tarel's method always has the highest value of MSEandthat means Tarel's method performs worse than others. Our score of MES is smaller in Fig.5 and 6 while is bigger in Fig.7. However, our score in Fig.7 is almost the same as He' method. In conclusion, it can consider that our method performs better than other's in MSE. From table 1, it is easily to find that Tarel's method always performs worsethan other's. our method has better than others, sometime it is as same as He's method.

Based on the analysis above, it can consider that our method is better than the two others and it is the same as which we analysis subjectively.

E. Running time

If a method cannot process in real time, we cannot applicate it in product. We chose different size of picture to run these three method. We run these three method 20 times and the get the average shown in table III.

TABLE III. RUNING TIME/S

Image size	Tarel's	He's	Ours
400×600	0. 9682	0.793 2	0.321 9
479×640	1.1363	1.041 0	0.445 9
768×1024	3.0295	2.601 9	0.930 8
1461×2560	13.5192	12.148	1.7567

When the image size become larger and larger, the running time of our method doesn't change very much but the others become slower and slower. That is because our method need just need to initial the model. Our method can process in real time.

IV. CONCLUSION

In this method, we propose a single image dehazing based on deep neural network that is to deal with haze image which token under the bad weather. We pay much time in training the mode that is for getting the depth map of input image. As a result, when we applicate our method is almost just need to initial the model that we have trained.The weight of our neural network that come from a real natural image and its depth, so that it can do good at getting depth map. Our method can do good in color restoration and dehzing.

ACKNOWLEDGEMENT

This research was financially supported by Science and Technology Program of Guangzhou, China （201605030013）.

REFERENCES

[1] Narasimhan S G, Nayar S K. Vision and the Atmosphere[J]. International Journal of Computer Vision, 2002, 48(3):233-254.

[2] Stark J A, Fitzgerald W J. An alternative algorithm for adaptive histogram equalization[J]. Graphical Models and Image Processing, 1996, 58(2): 180-185.

[3] Stark J A. Adaptive image contrast enhancement using generalizations of histogram equalization[J]. Image Processing, IEEE Transactions on, 2000, 9(5): 889-896.

[4] Rahman Z, Jobson D J, Woodell G A. Multi-scale retinex for color image enhancement[C]// International Conference on Image Processing, 1996. Proceedings. IEEE, 2002:1003-1006 vol.3.

[5] R. T. Tan. Visibility in bad weather from a single image. In Proc. CVPR, 2008

[6] R. Fattal. Single image dehazing. ACM Transactions on Graphics, 27(3), 2008

[7] K. He, J. Sun, and X. Tang. Single image haze removal using dark channel prior. In Preoccupy, 2009.

[8] K. He, J. Sun, and X. Tang. Single image haze removal using dark channel prior. IEEE TPAMI 33(12): 2341-2353, 2011.

[9] K. He, J. Sun, and X. Tang. Guided image filtering. In Proc. ECCV, pages 1-14, 2010.

[10] K. He, J. Sun and X. Tang. Guided image filtering. IEEE TPAMI, 35(6): 1397-1409, 2013.

[11] J. P. Tarel, and H. Nicolas. Fast visibility restoration from a single color or gray level image. In Proc. ICCV, 2009.

[12] Zhu Q, Mai J, Shao L. A Fast Single Image Haze Removal Algorithm Using Color Attenuation Prior.[J]. IEEE Transactions on Image Processing A Publication of the IEEE Signal Processing Society, 2015, 24(11): 3522-33.

[13] Stark J A, Fitzgerald W J. An alternative algorithm for adaptive histogram equalization[J]. Graphical Models and Image Processing, 1996, 58(2): 180-185.

[14] Narasimhan S G, Nayar S K. Contrast restoration of weather degraded images[J]. IEEE Transactions on Pattern Analysis & Machine Intelligence, 2003, 25(6):713-724.

[15] Eigen D, Puhrsch C, Fergus R. Depth Map Prediction from a Single Image using a Multi-Scale Deep Network[J]. Computer Science, 2014:2366-2374.

[16] Hu Zi'ang, Wang Weixing, Lu Jiangqiang, et al, Image Dehazing using Visual Information Loss Prior[J], Journal of Image and Gaphics, 2016, 21(6):711-722.22.