Dehazing of Satellite images using Convolutional Neural Network

[1]M.Vasudeva Reddy, [2]Dr.T.Ramashri
[1]Research Scholar, Rayalseema University,Kurnool, Andhra Pradesh, India.
[2] Professor, S.V.University, Tirupati, Andhra Pradesh, India.

Abstract: **Haze in remotely sensed images degrades the visual multispectral information. The literature reveals that haze removed images have problems like halo artifacts, colour distortion, etc. To overcome these problems, in this paper the fine scale transmission map of images is used in Convolutional neural network to restore the haze free images. Hazy images contain small value in only one-color alpha channel from Red, Blue, green RGB channel. The intensity of these pixels varies by air light depth map. Hence estimating these low value points of haze transmission map and an end-to-end encoder-decoder training model is utilized to achieve a high quality dehazed image. The experimental results reveal that this approach provides visually significant haze-free images by preserving the significant details when compared to DWT based Dehazing.**

Index Terms - **Haze, Dehazing, Discrete Wavelet Transform, Dark Channel Prior, Haar wavelet.**

I. INTRODUCTION

Haze represents the fog, mist, or other atmospheric phenomena which degrades outdoor images by reducing visibility in terms of both color and contrast. It is mainly generated by atmospheric scattering, usually modeled by using Mie theory which is caused by larger particles like dust, smoke, pollen grains, water droplets, etc. Haze is the natural process in which the dust and smoke [1] [2]. reflect the sunlight causing the vision loss. The visibility from the camera is faded as there exists interference with the environmental light source reflected by the dust particles. The blurred images gain noise and loses the colour attenuation.

If the image or scene is dull, then vision algorithms face many issues and do not show efficient performance. So, removing haze is needed for better results and efficiency. The bad images can be put to better use. The amount of dispersion depends upon the length of scene from the camera and this degradation is spatial-variant. Removal of haze from the image increases the visibility of hazy image caused by the atmospheric particles. The spatial distribution of the particles depends on weather conditions and the location of dust sources, which will be slower (on the scale of kilometers) than for land cover which changes at higher frequencies. Hence the low spatial frequency component is dominated by haze, while the high frequency components reflect the effect of land cover of satellite images with a spatial resolution of less than 100 m, like in Landsat, IRS sensor payloads, etc. Also the haze contamination is most pronounced in the visible bands, and is weaker or visually undetectable in the nearer shortwave- infrared parts of the spectrum.

This frequency dependency paves way for using the wavelets for dehazing algorithms [3] [4]. The images suffer from poor quality due to undesirable quantization artifacts and noises in heavily hazy regions or sky patches or even lose the original spectral or structural information. To overcome these problems, we propose a transmission map based Convolutional neural network for high quality image dehazing. This paper is organized as follows: section II deals with the literature survey of dehazing algorithms. The section III details with the proposed algorithm. The section IV shows the corresponding results followed by detailed discussion and finally the paper is concluded.

II. EXISTING DEHAZING ALGORITHMS

From literature, many authors proposed algorithms that helped the society to use practically in many applications. Earlier the problems were not only with satellite images, but also for railways where the track was not visible during heavy fog or mist conditions, in medical applications where the image captured by the camera used while doing operation usually happened to be dark and not clear, etc.

Due to the algorithms developed for Haze removal, all of these societal problems were solved to some extent. As Haze removal depends on the unknown depth information which changes at different locations. Earlier dehazing algorithms mainly exploit multiple images or extra information to recover the hazy image. Multiple images based dehazing methods remove the haze through handling two or more input images taken with different degrees of polarization filtered images [5], [6] or the same scene under different weather conditions [7], [8].

Another depth based dehazing techniques [9], [10] make use of scene depth information from known three-dimensional (3D) models or user inputs. But these methods impose limitations in real applications due to extra information or as multiple input images are not always available in databases. Hence restoration from a single image proved to be more attractive. Some researchers aimed at increasing the contrast and improving the color from the viewpoint of image enhancement like histogram-based [11], contrast based [12], fusion-based [13] [14] and so on. Unfortunately, enhancement-based dehazing methods cannot fully remove the haze owing to failing to consider image degradation mechanism. By contrast, physics-based dehazing algorithms first construct the haze imaging model, then estimate unknown parameters, and finally inverse the physical model to obtain the haze-free image starting from the reason of image degradation.

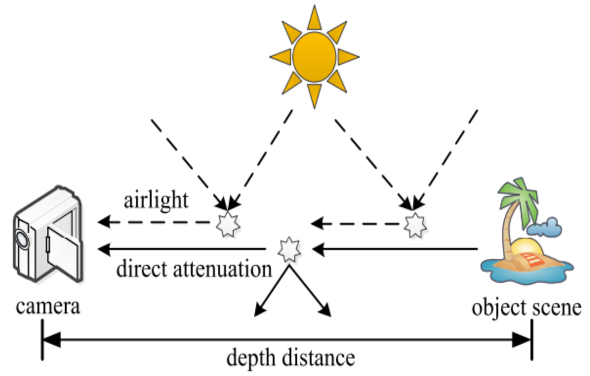

Fig.1: A Schematic Representation of Atmospheric Scattering Model

The schematic description of atmospheric scattering model is shown in figure 1[14]. The solid lines describe the direction attenuation part and dotted lines describe the air light part, respectively. As the visibility of bad weather images[15] is based on high contrast dehazed image and the air light intensity change depends on the distance from object to camera. The framework of MRF (Markov Random field) is used to enhance the output image by obtaining the detail and structure from the image. This method focuses on the enhancement of visibility; it does not aim for the recovery of reflected areas.

The scattered light [16] is removed in order to increase the vision and recover haze from the image by redefined image model that account for surface shading in addition to transmission function. Based on this image model, the image is divided into small parts of constant albedo. The light source ambiguity is removed by adding a function which require surface shading and medium transmission function to be locally statistically unrelated. Fattal used a physics-based approach to produce haze-free image and require statistical based assumption in the local patches which make it non-convenient.

Color attenuation prior model is used to remove haze from images [17]. A linear model with supervised learning is used for the scene depth of the hazy image. A link between the image and its depth map is established. This approach has high efficiency and better dehazed effect however did not perform well in all cases. The dehazed image can also be obtained by using the original degraded information, accurately[18] which aims at enhancement of visibility. Segmenting the super pixels technique is proposed to remove the haze from image [19]. The earlier methods for removing haze might not work under some conditions due to the noise distribution. So, to overcome the affect, an improved method by combining the segmented pixel with light intensity of a haze image was proposed to compute the sunlight instead of dark channel prior. They also proposed to estimates the transmission map. Color space conversion is done by converting RGB into HIS. In RGB channel, pick the brightest pixel and record the location of that particular pixel.

The worst weather conditions were considered by [20, 21] in which the images were taken in rainy weather which has noise and shady effect due to water droplets on the camera lens. The authors used polarization and dark channel prior method to solve the mentioned problems.

III. PROPOSED DEHAZING ALGORITHM

Haze removal methods fails under certain conditions like polarization techniques where the haze is removed by applying haze removal filter such as mean guided filter. To overcome this, they also computed the transmission map to further clear the visibility of the hazy image. The proposed training model first extracts the dehazed feature from the image using the convolution operation and fed-up the feature map to 1st hidden layer. As The features extracted will not be enough to remove haze from the given datasets, some high level features are also to be extracted. Hence the finer details of feature map are extracted in the second hidden layer. The output layer can check whether the input image is hazy or not as shown in Figure 2.

This dehazing method is applicable to images whose the low intensity pixel can be found from the hazy image by applying a filter. These intensity pixels further compute the transmission map which further improves visibility. By this, these particular pixels can give us the accurate computed haze model. After that, apply some methods on it and recover high quality dehazed image. The proposed method is applicable to handle the distant objects even in the very high turbid medium

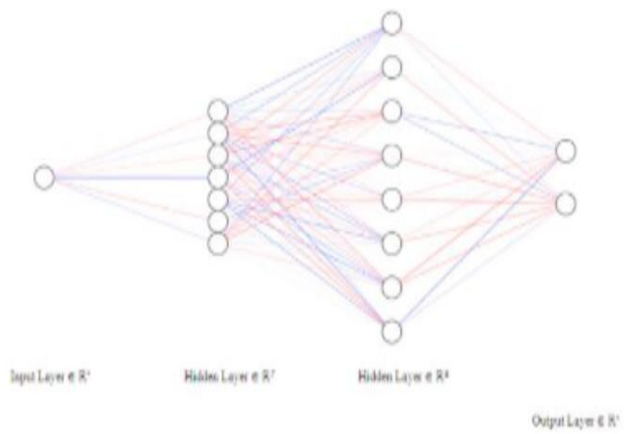

Fig. 2: Architecture of CNN

The encoding and decoding phase is shown in Figure 3, where CNN model contains 7 neurons in the 2nd hidden layer and 8 neurons in the 3rd hidden layer forwarding the information in a feed-forward manner which ensures the efficient method to pass the parameters in both forward and backward propagation pass.

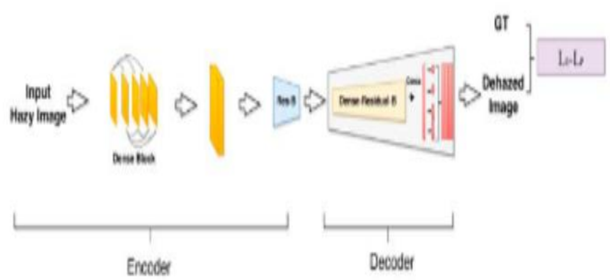

Fig. 3: Dehazing using CNN

The decoder function is similar to the encode phase except that it uses residual function which ensures that each hidden neuron is fully connected to all other neuron connected in the second layer as shown in Figure 3. The advantage of this function is that it improves the learning rate and converge our training data set model.

A non-linear relation is established between a hazy image and estimated ground truth. This relationship recovers a high quality dehazed image from a hazy image in an efficient manner. The proposed model involves an encoder-decoder structure using a deep neural network. The involvement of gradient descent increases the reliability of convergence of training dataset model. The mean squared error and residual loss function play a vital role in training of the dataset model. This approach is based on the mentioned hypothesized of the hazy images: in most of the non-environmental.

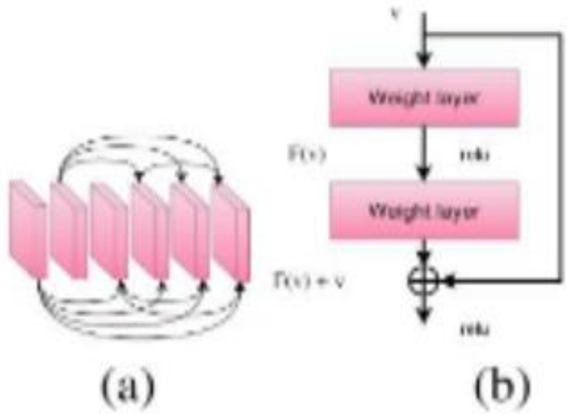

Fig. 4: (a) CNN Encoding Phase (b) Residual Function of CNN decoder

The above mentioned architecture is coded in matlab and tested for satellite images.

IV. RESULTS AND DISCUSSION

A. *Peak Signal to Noise Ratio (PSNR):-*

It is defined as difference between the real image and the fused image. PSNR is calculated by using equation (1)

$$\mathbf{PSNR(dB)} = \mathbf{20log}\frac{\mathbf{255}\sqrt{\mathbf{3MN}}}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(B'(i,j)-B(i,j)\right)^{2}}} \quad \ldots\ldots (1)$$

B-perfect fused image i - index of row, j-index of column M, N- No. of rows and columns

B. *Mean Squared Error (MSE):-*

In statistics, the mean squared error (MSE) or mean squared deviation (MSD) 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. In a sense, any measure of the centre of a distribution should be associated with some measure of error. If we say that the number t is a good measure of centre, then presumably we are saying that t represents the entire distribution better, in some way, than other numbers.

In this context, suppose that we measure the quality of t, as a measure of the centre of the distribution, in terms of the mean square error calculating by using eqn.(2)

$$\mathbf{MSE(t)} = \frac{1}{n}\sum_{i=1}^{k}\mathbf{f_i}\,(\mathbf{x_i}-\mathbf{t})^2 = \sum_{i=1}^{k}\mathbf{p_i}\,(\mathbf{x_i}-\mathbf{t})^2 \quad \ldots\ldots (2)$$

MSE (t) is a weighted average of the squares of the distances between t and the class marks with the relative frequencies as the weight factors. Thus, the best measure of the centre, relative to this measure of error, is the value of t that minimizes MSE. The coefficient of variation (CV) is the ratio of the standard deviation to the mean. The higher the coefficient of variation, the greater the level of dispersion around the mean. It is generally expressed as a percentage. Without units, it allows for comparison between distributions of values whose scales of measurement are not comparable.

When we are presented with estimated values, the CV relates the standard deviation of the estimate to the value of this estimate. The lower the value of the coefficient of variation, the more precise the estimate.

C. *Co-efficient of variation:-*

Mathematically, the standard formula for the co efficient of variation is expressed in the following way eqn. (3)

$$\text{Coefficient of variation} = \frac{\sigma}{\mu} \times \mathbf{100\%} \quad \ldots. (3)$$

Where

- $\boldsymbol{\sigma}$ **– the standard deviation**
- $\boldsymbol{\mu}$ **– the mean**

The overall image quality MSSIM is obtained by calculating the mean of SSIM values over all windows as shown eqn. (4)

$$\mathbf{MSSIM} = \frac{1}{P}\sum_{j=1}^{P}\mathbf{SSIM_j} \quad \ldots\ldots.. (4)$$

The performance of the proposed algorithm is verified on several satellite remote sensed images. The algorithm has been implemented and verified using Matlab. The performance parameters [10] such as Mean Absolute Error, Mean Square Error, and Peak Signal to Noise Ratio and Signal to Noise Ratio are calculated for the restoration of dehazed images as shown in figures 5,6,7, 8, and 9. The left most image represents the input image with haze, the middle image represents the DWT based dehazed image and the right most image represents the CNN based dehazed image.

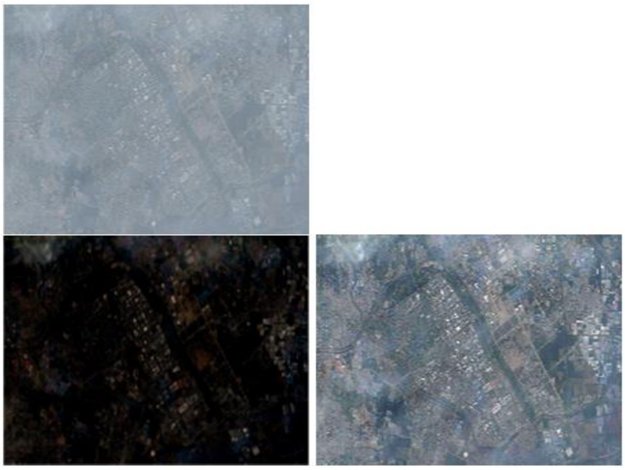

Fig. 5: Input and Output Images for input image - 1.

Fig. 6: Input and Output Images for input image - 2.

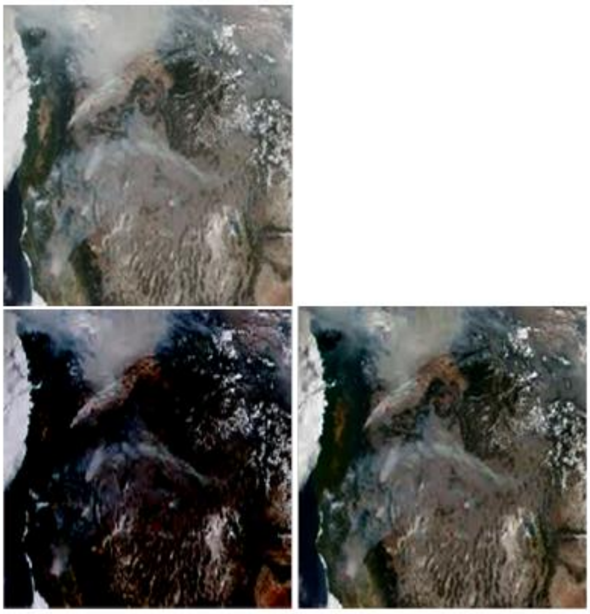

Fig. 7: Input and Output Images for input image - 3.

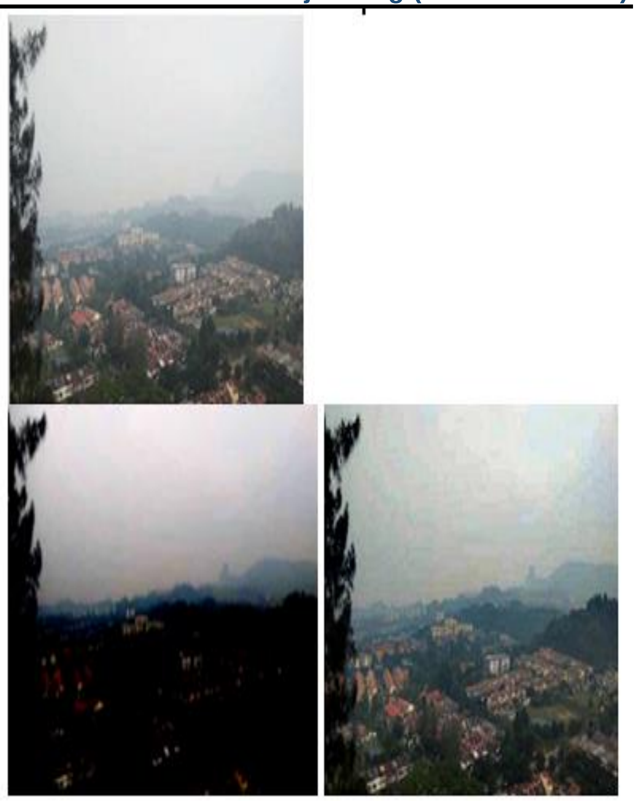

Fig. 8: Input and Output Images for input image - 4.

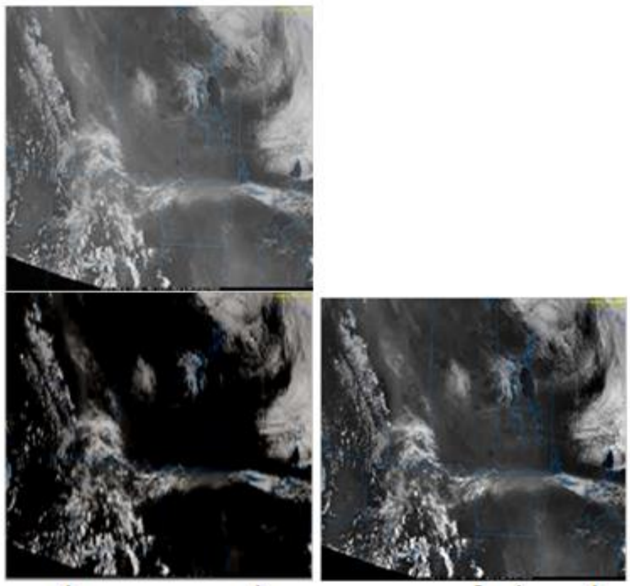

Fig. 9: Input and Output Images for input image - 5.

The images of dehazing done by CNN proves to be more clear than the DWT based dehazed images. Further the results are evaluated for various parameters like Mean Square Error, Peak Signal to Noise ratio, Coefficient of variance, structural Similarity index and mean Structural Similarity index which are consolidated in table 1.

Table - I: Comparison of proposed algorithm for various Parameters

Parameters	Image1		Image2		Image3		Image4		Image5	
	DWT	CNN	DWT	CNN	DWT	CNN	DWT	CNN	DWT	CNN
MSE	5.9851	1.5539	2.6497	1.2803	5.0524	1.5746	1.6866	1.8734	4.6474	1.8376
Peak Signal to Noise Ratio	20.3601	16.2167	13.8988	17.0568	11.0958	16.1590	5.8606	15.4045	11.4587	15.4884
Co-efficient of Variance	2.6567	20.2673	188.7799	31.1328	343.8651	61.1734	200.7562	61.6121	332.8755	60.1486
Structural Similarity Index	0.1087	0.1985	0.1168	0.3348	0.0813	0.5605	0.3431	0.2747	0.2358	0.4352
Mean Structural Similarity	0.2692	0.1283	0.2732	0.3064	0.2611	0.4548	0.4465	0.1821	0.4151	0.3410

From Table - I, the proposed algorithm proves to be a better choice for dehazing satellite images as the parameters show significant improvement of nearly on an average of 30%.

V.CONCLUSION

Haze is caused by dust, smoke, atmospheric scattering, etc which reduce the visibility. The hazed images contain small value in only one-color alpha channel from Red, Blue, green RGB channel whose intensity varies as air light depth map varies. Hence the low value points of haze transmission map are used along with an end-to-end encoder-decoder training model to obtain a high quality dehazed image. The proposed architecture based on Convolutional Neural Network utilizes these aspects and proved to be a better choice when compared to Discrete Wavelet Transform based dehazing algorithm. The algorithm was evaluated for parameters like Mean Square Error, Peak Signal to Noise ratio, Coefficient of variance, structural Similarity index and mean Structural Similarity index for proving it's efficiency.

REFERENCES

[1] S. G. Narasimhan and S. K. Nayar, “Contrast restoration of weather degraded images,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 25, no. 6, pp. 713–724, 2003.

[2] S. G. Narasimhan and S. K. Nayar, “Vision and the atmosphere,” International Journal of Computer Vision, vol. 48, no. 3, pp. 233–254, 2002.

[3] Y. Y. Schechner, S. G. Narasimhan, and S. K. Nayar, “Instant dehazing of images using polarization,” in Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR '01), vol. 1, pp. 325–332, IEEE, Kauai, Hawaii, USA, 2001.

[4] J. G. Walker, P. C. Y. Chang, and K. I. Hopcraft, “Visibility depth improvement in active polarization imaging in scattering media,” Applied Optics, vol. 39, no. 27, pp. 4933–4941, 2000.

[5] J. Kopf, B. Neubert, B. Chen et al., “Deep photo: model-based photograph enhancement and viewing,” ACM Transactions on Graphics, vol. 27, no. 5, article 116, 2008.

[6] K. He, J. Sun, and X. Tang, “Single image haze removal using dark channel prior,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR '09), pp. 1956–1963, IEEE, San Francisco, Calif, USA, June 2009.

[7] C. X. Xiao and J. J. Gan, “Fast image dehazing using guided joint bilateral filter,” Visual Computer, vol. 28, no. 6–8, pp. 713–721, 2012.

[8] J. W. Zhang, L. Li, G. Q. Yang, Y. Zhang, and J. Z. Sun, “Local albedo-insensitive single image dehazing,” Visual Computer, vol. 26, no. 6-8, pp. 761–768, 2010.

[9] C. O. Ancuti and C. Ancuti, “Single image dehazing by multi-scale fusion,” IEEE Transactions on Image Processing, vol. 22, no. 8, pp. 3271–3282, 2013.

[10] Z. Wang and Y. Feng, “Fast single haze image enhancement,” Computers and Electrical Engineering, vol. 40, no. 3, pp. 785–795, 2014.

[11] Manisha A. Wakure, Dr. Anilkumar N. Holambe,“ A Steganographic Method for Transmitting Images Based on Discrete Wavelet Transform Using Three Level and Single Level Wavelet Decomposition” in International Journal of Advanced Research in Computer Science and Software Engineering, Volume 6, Issue 3, March 2016.

[12] Mingye Ju, Zhenfei Gu, Dengyin Zhang, and Haoxing Qin, " Visibility Restoration for Single Hazy Image Using Dual Prior Knowledge", Hindawi Mathematical Problems in Engineering Volume 2017, Article ID 8190182, 10 pages.

[13] Dilbag Singh, Vijay Kumar," Dehazing of outdoor images using notch based integral guided filter ", Multimedia Tools and Applications, October 2018, Volume 77, Issue 20, pp. 27363-27386.

[14] Yun Liu, Jinxia Shang, Lei Pan, Anzhi Wang, and Minghui Wang, " A Unified Variational Model for Single Image Dehazing ", IEEE Access 2019, Volume 7, pp. 15722-15736.

[15] Hsu, E., et al.,"Light mixture estimation for spatially varying white balance", ACM transactions on graphics (TOG), ACM, 2008.

[16] Gibson, K. B., et al. "An investigation of dehazing effects on image and video coding." IEEE Transactions on Image Processing21(2): 662-673,2012.

[17] Nayar, S. K. and S. G. Narasimhan, "Vision in bad weather". Computer Vision, 1999. The Proceedings of the Seventh IEEE International Conference on, IEEE,1999.

[18] Peng, L., et al., "Single image fog removal based on dark channel prior and local extrema." American Journal of Engineering and Technology Research Vol12(2), 2012.

[19] Scharstein, D. and R. Szeliski, "A taxonomy and evaluation of dense two-frame stereo correspondence algorithms." International journal of computer vision47(1-3): 7-42, 2002.

[20] Schechner, Y. Y., et al., "Instant dehazing of images using polarization". Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on, IEEE.

[21] Sun, C.-C., et al. "Single image fog removal algorithm based on an improved dark channel prior method". Intelligent Signal Processing and Communication Systems (ISPACS), 2016 International Symposium on, IEEE, 2016.