Augmented Approach on Single Image Dehazing using R-CNN

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Abstract : Images captured beneath outside scenes sometimes suffer from low distinction and restricted visibility thanks to suspended region particles, that directly affects the standard of photos. Despite varied image dehazing ways are projected, effective hazy image restoration remains a difficult downside. Existing learning-based ways sometimes predict the medium transmission by Convolutional Neural Networks (CNNs), however ignore the key international region light-weight. completely different from previous learning-based ways, we have a tendency to propose a versatile cascaded CNN for single hazy image restoration, that considers the medium transmission and international region light-weight collectively by 2 task-driven subnet works. Specifically, the medium transmission estimation subnetwork is galvanized by the densely connected CNN whereas the worldwide region light-weight estimation subnetwork may be a light-weight CNN. Besides, these 2 subnetworks square measure cascaded by sharing the common options. Finally, with the calculable model parameters, the haze-free image is obtained by the region scattering model inversion, that achieves a lot of correct and effective restoration performance. Qualitatively and quantitatively experimental results on the artificial and real-world hazy pictures demonstrate that the projected methodology effectively removes haze from such pictures, and outperforms many progressive dehazing ways

***IndexTerms* - Image haze removal, image enhancement, DCP,CNN,RCNN.**

I. Introduction

Recent years, we've got witnessed a speedy development of wireless network technologies and mobile devices equipped with numerous cameras that have revolutionized the approach individuals take and share multimedia system content [1], [2]. However, out of doors pictures (e.g., Figure 1) typically suffer from low distinction, obscured clarity, and light colors because of the floating particles within the atmosphere, like haze, fog, or dust that absorb and scatter light-weight. These degraded out of doors pictures not solely have an effect on the standard of photos [3] however conjointly limit the applications in urban transportation [4], video analysis [5], visual police investigation [6], and driving help [7]. Therefore, image dehazing or image defogging has become a promising analysis space. in addition, image dehazing ways conjointly offer reference values for the underwater image sweetening and restoration analysis field [8], [9]. However, it's still a difficult task since the haze concentration is troublesome to estimate from the unknown depth within the single image. Single hazy image restoration ways sometimes got to estimate 2 key elements within the hazy image formation model (i.e., medium transmission and world part light). to realize these 2 elements, ancient prior-based ways either attempt to realize new forms of haze connected priors or propose new ways in which to use them. However, haze connected priors don't forever hold, particularly for the variable scenes. Against this, to get additional sturdy and correct estimation, the learning-based ways explore the relations between the hazy pictures and also the corresponding medium transmission in data-driven manner.

Figure 1 Outdoor Hazy images

However, most of the learning-based ways estimate the medium transmission and world part light-weight on an individual basis, and don't take into account the joint relations of them. Additionally, separate estimation for the medium transmission and world part light-weight limits the flexibleness of previous ways. Thus, it evokes U.S. to explore the joint relations between the medium transmission and also the world part light-weight, and the way to directly map Associate in nursing input hazy image to its medium transmission and world part light-weight at the same time in pure data-driven manner.

In nearly each sensible state of affairs the sunshine mirrored from a surface is scattered within the atmosphere before it reaches the camera. this can be thanks to the presence of aerosols like mud, mist, and fumes that deflect light-weight from its original course of propagation. In long distance photography or foggy scenes, this method contains a substantial impact on the image within which contrasts square measure reduced and surface colours become faint. Such degraded pictures typically lack visual vividness and charm, and furthermore, they provide a poor visibility of the scene contents. This impact could also be associate annoyance to amateur, commercial, and inventive photographers moreover as undermine the standard of underwater and aerial photography. this could even be the case for satellite imaging that is employed for several functions together with making and internet mapping, land-use coming up with, archeology, and environmental studies. So main objective of this paper is to overcome the current problems of haze removal , remove haze from real time images.

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II. Overview of Dehazing Methods

Table 1. Dehazing Methodologies

Technique	Advantages	Disadvantages	Applications
Optical model	(a) Signficant results for thin haze	a) Transmission and surface shading are locally uncorrelated. (b) The absence of multiplicative variation in significant portions.	Natural images
Visibility restoration	(a) Good speed	(a) Edge preservation is not considered. (b) Not effective for large haze gradients	Lane-marking extraction
Multi-scale retinex	(a) No user interaction is needed. (b) Faster speed	] (a) Halo artifacts. (b) Not effective for large haze gradients	51Natural images
Dark channel prior	(a) High-quality haze-free image	(a) Failure in the sky (bright) regions. (b) Fail to restore image under inhomogenious haze. (c) Edge preservation is not considered.	Outdoor images
Image enhancement	(a) No color distortion (b) Poor speed	(a) Edge preservation (b) Noise suppersion (c) Over/under enhancement	Intelligent transportation vision system
Filtering	(a) Efficient noise supperssion (b) Edge preservation	(a) Poor speed (b) Halo artefacts (c) Not effective for large haze gradients	Underwater image Enhancement
Deformed haze model	(a) No color drift	(a) May introduce certain artifacts (b) Fail to dehaze image with large haze gradient (c) Sometimes may lead over/ under enhance results	Remotly sensed images
Edge preserving	(a) Efficient edge preservation (b) Low color distortion	(a) Poor computation time	Natural images
Change of detail prior	(a) Stable to local areas	(a) Cannot preserve the edges (b) Color distortion	Natural images
Linear transformation	(a) Efficient for sky area (b) Efficient speed	(a) Potential edges may degraded	Natural images
Look-up-table	(a) Minimum computation time (b) Efficient brightness	(a) Edge preservation (b) Color distortion	Natural images
Multiple scattering model	(a) Decreases the color distortion in sky area (b) Ability to overcome the halo artifacts	(a) Not efficient for estimating the atmospheric veil	Natural images
Intervention refinement filter	(a) Edge preservation (b) High contrast	(a) Halo artifacts (b) Lower computational speed	Natural images
Meta-heuristic techniques	(a) Optimistic results	(a) Premature convergence (b) Local optima	Natural images

Super-wised learning Natural images	(a) Efficient for all kind of images		
Wavelet transform	(a) Large set of images required for training (b) Learning models are complex and leads to a lower computational speed	(a) Efficient noise suppression (b) Edge preservation (a) May introduce certain artifacts (b) Fail to dehaze image with large haze gradient (c) Sometimes may lead over/ under enhance results	Natural images
Fusion based	(a) Have more efficient results than single image dehazing technique.	(a) Models are complex and leads to a lower speed.	Natural images
Variational model based	(a) Overcome the physical assumptions failure issue (b) over-enhancement problem	(a) Models are complex and leads to a lower speed. Natural images	Natural images

III. Related Work

Numerous image dehazing strategies are planned within the recent decade [10]. These strategies will be roughly classified into four categories: further information-based strategies [11]–[14], distinction enhancement-based strategies [15] [18], prior-based strategies [19]–[20], and learning-based strategies [2]–[3]. though further information-based strategies are able to do spectacular dehazing performance, they show limitations in real-life applications. In general, distinction enhancement-based strategies manufacture underneath or over increased regions, color distortion, and artifacts thanks to failing to contemplate the formation principle of the hazy image and image degradation mechanism. As follows, we tend to chiefly introduce the prior-based and learning-based strategies and summarize the prevailing issues.

Prior-based strategies formulate some restrictions on the visual characteristics of hazy pictures to resolve associate ill-posed downside, that has created important progress recently. Dark channel previous (DCP) technique planned by He et al. [20] is one in every of classical prior-based strategies, that relies on statistics that a minimum of one channel has some pixels with terribly low intensities in most of non-haze patches. Supported the DCP, the medium transmission and international region lightweight ar roughly calculable. Finally, the dehazed image is achieved by the calculable medium transmission refined by soft matting [15] or guided filter [36] further because the calculable international region lightweight consistent with associate region scattering model. Although, the DCP technique will get outstanding dehazing leads to most cases, it tends to over-estimate the thickness of haze, that ends up in color casts, particularly for the sky regions.

Subsequently, several ways square measure applied to reinforce the performance of the first DCP technique. Zhu et al. [14] projected a straightforward nonetheless effective previous (i.e., CAP) for image dehazing. The scene depth from the camera to the article of a hazy image is sculpturesque during a linear model supported the CAP wherever unknown model parameters square measure calculable by a supervised learning strategy. Albeit prior-based ways have achieved exceptional progress, they still have some limitations and want to be more improved. As an example, their performance is very depending on the accuracy of the calculable medium transmission and international atmospherically light-weight, that is tough to attain once the priors square measure invalid. Additionally, they additionally might entail high computation price that makes it unfeasible for period applications.

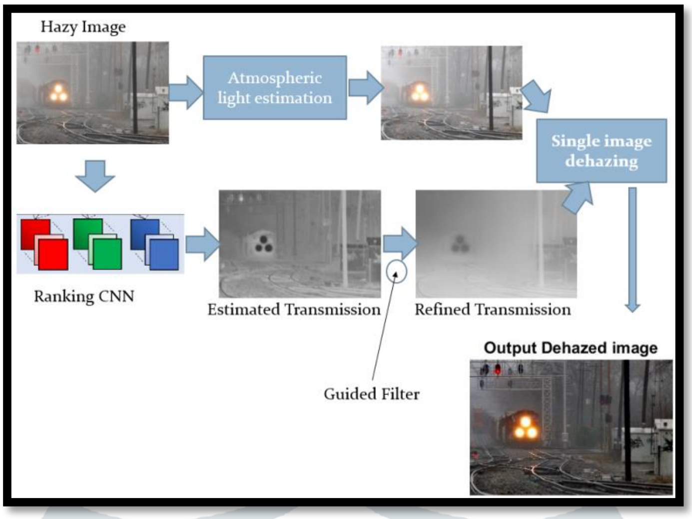
With fast development of learning technology in laptop vision tasks [7], [8], the learning-based ways are adopted in image dehazing. As an example, Tang et al. [2] extracted multi-scale handcrafted haze-relevant options, then used random forests regressor [3] to find out the correlation between the handcrafted options and therefore the medium transmission.

However, these handcrafted options square measure less effective and scant for a few difficult scenes, that limits its performance. Generally, for the handcrafted features-based ways, inappropriate feature extraction typically ends up in poor dehazing results. Completely different from the handcrafted options, Cai et al. [10] projected a CNN-based image dehazing technique, named DehazeNet, that trained a regression to predict the medium transmission. The DehazeNet includes four ordered operations, i.e., feature extraction, multi-scale mapping, native extreme, and non-linear regression. The coaching dataset is generated by haze-free patches collected from web, random medium transmission price, and stuck international atmospherical light-weight price (i.e., 1) supported associate degree atmospherical scattering model.

With the optimized network weights, the medium transmission of associate input hazy image are often calculable by network forward propagation. After that, the target-hunting filtering [6] as postprocessing is employed to get rid of the interference artifacts of the calculable medium transmission caused by the patch based mostly estimation. to boot, the authors applied associate empirical methodology to estimate the world atmospherical light-weight. Similar with DehazeNet [10], Ren et al. [3] designed a multi-scale CNN for single image dehazing. Recently, Li et al. [13] projected associate all-in-one deep model for single image dehazing, that directly generated the clean image victimization CNN. to boot, such all-in-one spec has been extended to the video dehazing [14], that fills within the blank of video dehazing by deep learning ways. For CNN-based ways, the accuracy of the calculable medium transmission and therefore the dehazing performance got to be additional improved, particularly for varied scenes. Moreover, most of CNN-based ways estimate the world atmospherical light-weight by the empirical ways, that limits the flexibleness of network and therefore the accuracy of restoration.

IV. PROPOSED METHOD

Figure 2 Proposed Flow



Algorithm for proposed work

Define abbreviations and acronyms the first time they are used in the text,

a) Preprocessing

- Input hazy image from the user
- Use **im2double** to converts the intensity image I to double precision
- Initialize gamma coefficient used for dehazing (0.8-1.5)

If the input is very hazy, large gamma

Otherwise static 1.3 for every image

b) Implementation of Dark channel prior

- Using window size , padded array
- For each patch finalize the minimum of particular patch.
- min (rgb, local patch)
  - – min (r, g, b)

min (local patch) = min filter.

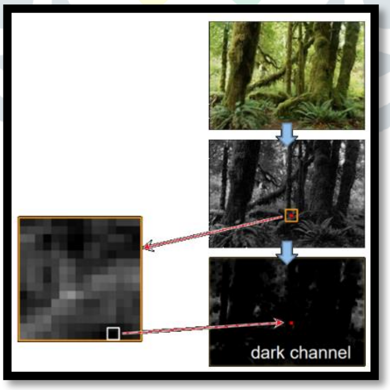


Figure 3. Dark Channel Prior

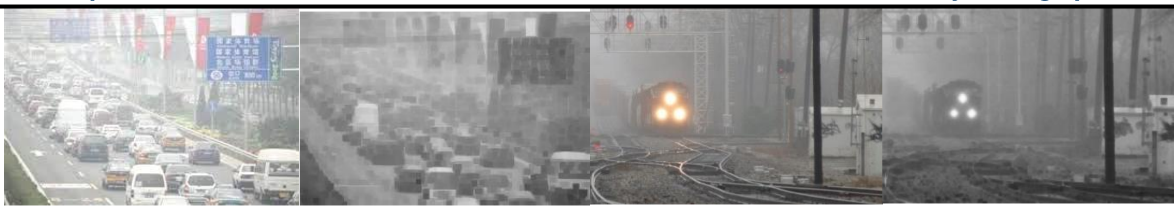


Figure 4. Results of Dark Channel Prior

a) Atmospheric light estimation

- Using White Balance

Figure 5. Results of Estimated Light

c) MatConvNet integration for CNN execution

MatConvNet is a MATLAB toolbox implementing Convolutional Neural Networks (CNNs) for computer vision applications.

d) Load Ranking CNN parameters for forward Propagation

- Applying 15 layers for forward Propagation
- MatConvNet includes a variety of layers, contained in the matlab/ directory, such as
  - vl_nnconv (convolution),
  - vl_nnconvt (convolution transpose or deconvolution),
  - vl_nnpool (max and average pooling),
  - vl_nnrelu (ReLU activation),
  - vl_nnsigmoid (sigmoid activation),
  - vl_nnsoftmax (softmax operator),
  - vl_nnloss (classification log-loss),
  - vl_nnbnorm (batch normalization),
  - vl_nnspnorm (spatial normalization),
  - vl_nnnormalize (local response normal
- Plot Feature rank matrix

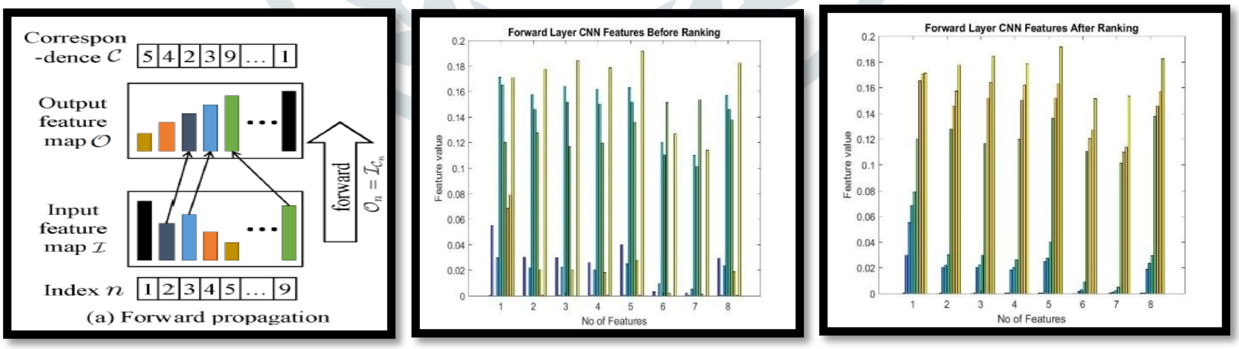


Figure 6. Forward Layer Ranking CNN

e) Load Ranking CNN parameters for Backword Propagation

- Applying 15 layers for Backward Propagation

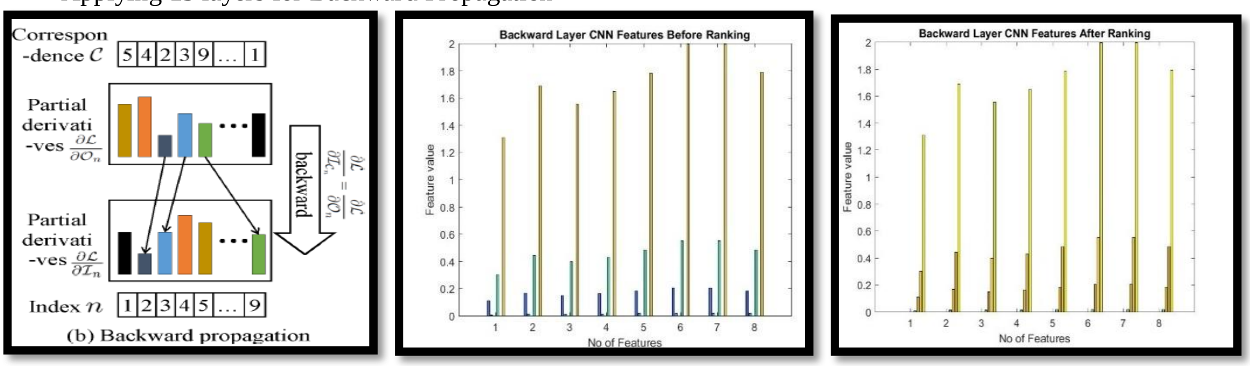


Figure 7. Backward Layer Ranking CNN

f) Transmission post- processing

- Air light estimation
  Optimization-based processing
- Applying Guider Filter

Figure 8. Estimated and Refined Transmission Map

g) Single image dehazing

Using R, G & B Feature
With re-define transmission map

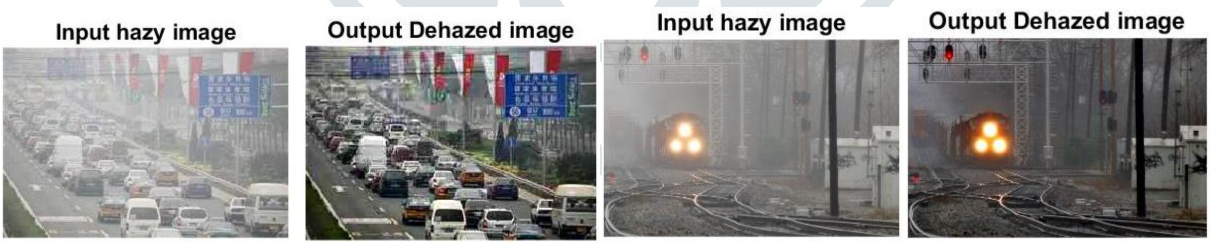


Figure 9. Final Dehazed Images

IV. RESULTS AND DISCUSSION

Table 1. Result Analysis

Sr.No.	Image Name	Elapsed Time (sec)	PSNR (+dB)	MSE	RMSE	MSSIM
1	city.jpg	52.963193	63.19718	0.09416	0.30686	0.99874
2	cones.jpg	39.244177	64.37151	0.07185	0.26806	0.99904
2	Car.jpeg	34.686641	61.31047	0.1454	0.38131	0.99805

Moreover, the originated has worked upon atleast forty four pictures with varied resolutions and sizes to visualize the potency of the code. in line with the final laws of values came by the parameters, values of MSSIN, MSE, RMSE should be as low as doable. and also the price of PSNR should be high.This is clearly seen within the higher than chart. The values for MSE, RMSE and SSIM shown by Series three, series 4, series five severally ar thus low that they're virtually not visible within the graph plot. Next, PSNR will be seen systematically high higher than vary of sixty that indicates higher results.

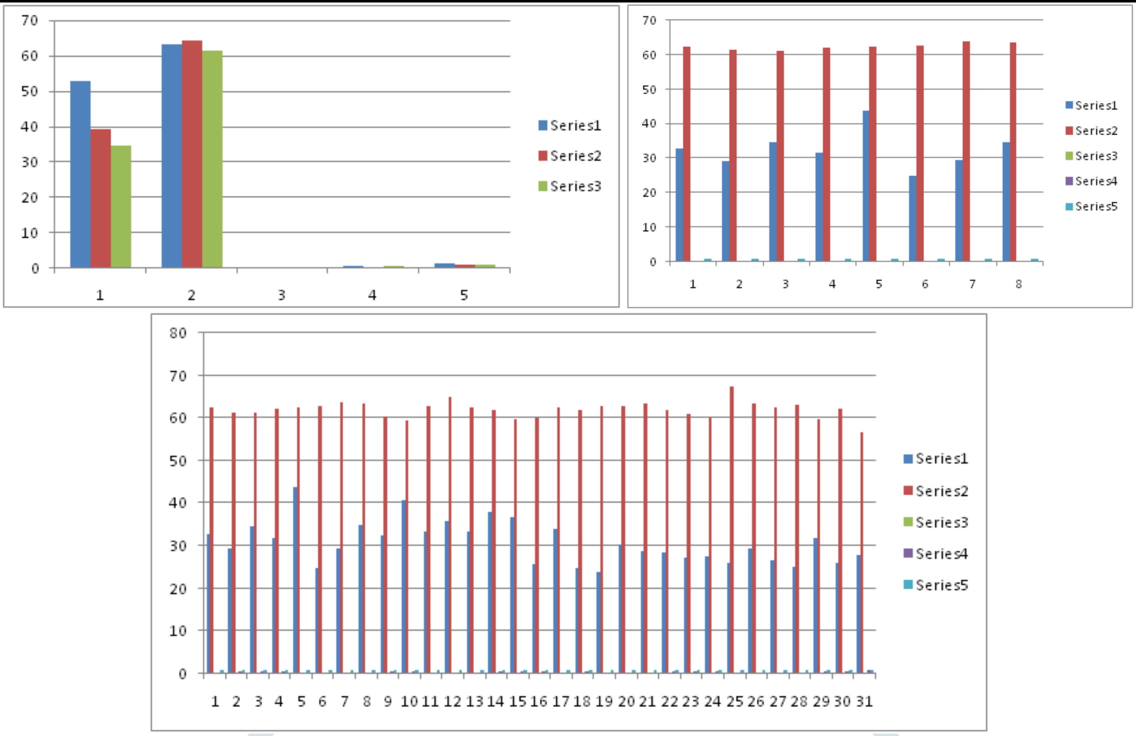


Figure 10. Result analysis

V. Conclusion

We have mentioned why haze removal is needed why there's a scope of analysis during this space. We've got conjointly analyze varied techniques that are wont to take away haze from pictures and compare them supported totally different aspects. Then we've got outlined planned framework that embody ranking based mostly haze removal that's a novel approach which will improve the performance of the image. we are going to conjointly add the removal technique to get rid of snow or rain strikes thus any atmosphere based mostly clamant image are often increased victimization our formula. For the mentioned information within the on top of chapter, we've got tried to implement the procedure on around fifty pictures within the initial section. For all the pictures we've got calculated MSE, RMSE, PSNR, MSSIN and Time march on. Thus over that a verified worth of PSNR is obtained within the best time potential. the worth of MSSIM as mentioned within the graphs have tested that the enforced work has the tendency to dehaze the image within the smallest time potential. In future we can extend this work for video dehazing.

References

[1] Ali, A. 2001.Macroeconomic variables as common pervasive risk factors and the empirical content of the Arbitrage Pricing Theory. Journal

[2] B. Cai, X. Xu, K. Jia, C. Qing, and D. Tao. Dehazenet: An end-to-end system for single image haze removal. IEEE Transactions on Image Processing, 25(11):5187 – 5198, Nov 2016.

[3] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille. Semantic image segmentation with deep convolutional nets and fully connected crfs. In International Conference on Learning Representations, 2015.

[4] D. Cho, Y.-W. Tai, and I. Kweon. Natural image matting using deep convolutional neural networks. In European Conference on Computer Vision, volume 9906 of Lecture Notes in Computer Science, pages 626–643. 2016.

[5] D. Erhan, C. Szegedy, A. Toshev, and D. Anguelov. Scalable object detection using deep neural networks. In IEEE Conference on Computer Vision and Pattern Recognition, pages 2155–2162, June 2014.

[6] C. Farabet, C. Couprie, L. Najman, and Y. LeCun.

[7] Learning hierarchical features for scene labeling. IEEE Transactions on Pattern Analysis and Machine Intelligence, 35(8):1915–1929, Aug. 2013

[8] J. Xie, L. Xu, and E. Chen. Image denoising and inpainting with deep neural networks. In Advances in Neural Information Processing Systems, pages 341–349. 2012.

[9] H. Xu, G. Zhai, X. Wu, and X. Yang. Generalized equalization model for image enhancement. IEEE Transactions on Multimedia, 16(1):68–82, 2014.

[10] Q. Yan, L. Xu, and J. Jia. Dense scattering layer removal. In SIGGRAPH Asia Technical Briefs, pages 14:1–14:4 , 2013.

[11] M. Zeiler and R. Fergus. Visualizing and understanding convolutional networks. In European Conference on Computer Vision, volume 8689 of Lecture Notes in Computer Science, pages 818–833. 2014.

[12] Q. Zhu, J. Mai, and L. Shao. A fast single image haze removal algorithm using color attenuation prior. IEEE Transactions on Image Processing, 24(11):3522–3533 , Nov 2015.

[13] K. B. Gibson and T. Q. Nguyen. Fast single image fog removal using the adaptive wiener filter. In IEEE International Conference on Image Processing, pages 714–718, Sept. 2013.

[14] K. B. Gibson, D. T. Vo, and T. Q. Nguyen. An investigation of dehazing effects on image and video coding. IEEE Transactions on Image Processing, 21(2):662–673 , Feb. 2012.

[15] K. He, J. Sun, and X. Tang. Single image haze removal using dark channel prior. In IEEE Conference on Computer Vision and Pattern Recognition, pages 1956–1963 , June 2009.

[16] K. He, J. Sun, and X. Tang. Guided image filtering. IEEE Transactions on Pattern Analysis and Machine Intelligence, 35(6):1397–1409, June 2013.
[17] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In IEEE Conference on Computer Vision and Pattern Recognition, June 2016.
[18] Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell. Caffe: Convolutional architecture for fast feature embedding. arXiv preprint arXiv:1408.5093, 2014
[19] J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. In IEEE Conference on Computer Vision and Pattern Recognition, June 2015.
[20] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In Advances in Neural Information Processing Systems, pages 1097–1105. 2012