18BCE2354

Single Image Dehazing using Dark Channel Prior

And Color Attenuation Prior

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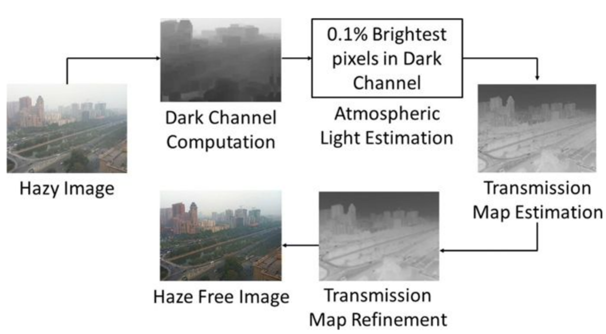
Synopsis

To detect or remove the haze from a single image is a challenging task in computer vision, because little information about the scene structure is available. In spite of this, the human brain can quickly identify the hazy area from the natural scenery without any additional information. This inspired us to conduct a large number of experiments on various hazy images to find the statistics and seek a new prior for single image dehazing. Interestingly, we find that the brightness and the saturation of pixels in a hazy image vary sharply along with the change of the haze concentration. We have proposed a very simple but powerful prior, called the dark channel prior, for single image haze removal. The dark channel prior is based on the statistics of outdoor haze-free images. Combining the prior with the haze imaging model, single image haze removal becomes simpler and more effective. Since the dark channel prior is a kind of statistics, it may not work for some particular images. When the scene objects are inherently similar to the atmospheric light and no shadow is cast on them, the dark channel prior is invalid. The dark channel of the scene radiance has bright values near such objects. As a result, our method will underestimate the transmission of these objects and overestimate the haze layer. Moreover, as our method depends on the haze imaging model, it may fail when this model is physically invalid. First, the constant-air light assumption may be unsuitable when the sunlight is very influential. We have also proposed a novel linear colour attenuation prior, based on the difference between the brightness and the saturation of the pixels within the hazy image. By creating a linear model for the scene depth of the hazy image with this simple but powerful prior and learning the parameters of the model using a supervised learning method, the depth information can be well recovered. By means of the depth map obtained by the proposed method, the scene radiance of the hazy image can be recovered easily. Experimental results show that the proposed approach achieves dramatically high efficiency and outstanding dehazing effects as well. One of the most important advantages of this model is that it has the edge-preserving property.



Graphical Abstract for DCP and CAP

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WHAT YOU OR YOUR GROUP HAS DONE IN REVIEW 0 (FIRST REVIEW)?

In the first review(Review 0), my team and I had proposed the topic we had chosen for our project, which is “*Single image dehazing using Dark Channel Prior and Colour Attenuation Prior”.* We had explained in brief what is the problem which we were going to solve, the principles behind the methods of approach, the applications of the project, its various merits and demerits etc. We also had backed our project based on three research papers, among many others that we were going to refer to, based on the aforementioned two methods- “Dark Channel Prior” and “Colour Attenuation Prior”. We had submitted a report of all these items, and had also attached the front-page copies of the three papers mentioned earlier.

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WHAT YOU OR YOUR GROUP HAS DONE IN REVIEW 1 (SECOND REVIEW)?

In the second review(Review 1), my team and I had presented to you the topic, which is "*Single Image Dehazing using Dark Channel Prior and Colour Attenuation Prior"*, and had explained to you, in detail, about the aforementioned two methods, "Dark Channel Prior" and "Colour Attenuation Prior".

In a nutshell, our project aims to find or recover images with proper colour saturation and other original characteristics by removing the effects of fog or haze present in the image. We had then explained to you the principles working behind the two methods, and had also explained to you the applications of our project, some of which includes dehazing images from traffic cameras or weather balloon camera feeds, and using it as a pre-processing step for further analysis of images in various research fields, among many others.

We had shown you the research papers we were referring to, in our approach of implementation of the project.

We had also shown you the architecture of our project, using various block diagrams and flowcharts, clearly elucidating where or how each part works in the overall working of the project.

In the end, we had also mentioned about implementing the project using the *python* language, and also mentioned using the *Open-CV* library for implementing various operations on the images.

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Review-3

1. INTRODUCTION-

Images that are captured in bad weather such as haze and fog are not clearly expressed and hence not so comprehensible. Such images are reduced in quality to a great degree due to the scattering of atmosphere that in turn reduces contrast and visibility. Fog leads to whiteness in the image as well as low contrast. Haze is an atmospheric occurrence which fades the clearness and precision of image because of dust or smoke which are minute portions of matter. It affects not only the visibility but also complicates post processing of image and implementation of numerous Computer Vision Algorithms. In this paper, we present an efficient and productive fog elimination approach when an image is taken in as input. On the basis of estimated transmission or depth map, this procedure re-establishes the hazy or foggy image. We have proposed a Dark Channel Prior and Color Attenuation Prior approach which is beneficial for clearing the degraded image. We eliminate haze from unclear images so that the characteristics and attributes of images are improved. Our acquired result is a haze free and fog free image by these techniques. The implementation and design are done with the help of python.

a. MOTIVATION

The presence of environmental disturbances such as haze and smog give outdoor images and videos undesirable characteristics that affect the ability of computer vision systems to detect patterns and perform an efficient feature selection and classification. These characteristics are caused by the decrease in contrast and color modification originated by the presence of suspended particles in the air. Hence, the task of removing the haze, fog, and smog (de-hazing), without compromising the image information, takes on special relevance. Therefore, to improve the performance of systems such as surveillance, traffic, self-driving vehicles is essential to develop new and better dehazing methods. This problem has been studied extensively in the literature with two main approaches: methods that use multiple images and methods that use just a single image.

b. CONTRIBUTION

Our “Deep-DCP” method offers the following contributions:

1) It provides state-of-the-art results in outdoor single image dehazing, outperforming both prior-based and fully-supervised DNN methods.

2) It achieves an impressive ~ 6.5dB boost in outdoor PSNR over classical DCP, validating an effective regularization.

3) It treats the sky successfully where DCP typically fails.

4) It is the first to perform unsupervised training in single image dehazing, reducing the need in synthetic data.

5) It does not require an explicit optimization for each image as DCP, but rather learns the underlying transformation during training, requiring a fast forward-pass during the test.

6) It offers a generic methodology of unsupervised training with energy functions and can be applied to any successful energy function.

c. Organization of Report-

2. Literature Survey
3. Background of Project work
4. Proposed Work
5. Evaluation and Result Analysis
6. Comparison with Existing Work
7. Overall Discussion
8. Conclusion
9. References

2. Literature Survey-

References	Methods used	Evaluation	Merits and Demerits
the paper ,'Hybrid Single Image De-hazing with Bright Channel and Dark Channel Prior'	J.Jackson, O.Ariyo, K.Acheampong, M.Boakye, E.Frimpong, E.Ashalley, and Y.Rao propose a method which uses both DCP and BCP to achieve air-light approximations	It uses a fast guided filtration method for a better transmission map refinement	There are chances of loss of precision.
2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC) 21 - 23 Dec 2017, Dhaka, Bangladesh 413	In this paper, we proposed an effective algorithm for haze removal focusing on the removal of major demerits remaining in previous works.	Describing our method that can automatically determine the patch size and sky region's degradation effect based on haze characteristics	PROS: On the basis of both subjective and objective measures, our method gives better results compared to some existing methods. CONS: It does not support multiple images.

Efficient single image dehazing by modifying the dark channel prior Sebastián Salazar-Colores1, Juan-Manuel Ramos-Arreguín2* , Jesús-Carlos Pedraza-Ortega2 and J Rodríguez-Reséndiz 2	We have reached to the result that the method of dark channel prior is nothing but a kind of statistics related to outdoor de-hazed images. The extent of fog can be known and a clear defogged image can be acquired.	The dark pixels give a valid estimation of the amount of fog transmission. Combination of a delicate interpolation system and haze imaging model can give a clear fog free picture	Pros: Analyzing the experimental results of the quantitative analysis performed, it is observed that the proposed algorithm generates competitive results against four state of-the-art algorithms without the need for a refinement stage
Unsupervised Single Image Dehazing Using Dark Channel Prior Loss Alona Golts, Daniel Freedman, and Michael Elad, Fellow	Have describe their method for single image dehazing, including the driving force of our unsupervised loss function, the Dark Channel Prior its implementation as a loss function for training a CNN .	Our method relies on the well-known Dark Channel Prior (DCP) and manages to improve it considerably	We have presented a method of unsupervised training of deep neural networks for the purpose of single image dehazing. In addition to provide state-of-the-art performance in outdoor scenarios, our method also eliminates the need for synthetic training sets.

3. Background of the project work-

a. Various Components of Project-

The haze imaging equation is given by:

$$I(x) = J(x)t(x) + A(1 - t(x)).$$

. The variables are explained in the following:

• x = (x, y) is a 2D vector representing the coordinates (x, y) of a pixel's position in the image.

• I represent the hazy image observed. I(x) is a 3D RGB vector of the color at a pixel.

• J represents the scene radiance image. J(x) is a 3D RGB vector of the color of the light reflected by the scene point at x. It would be the light seen by the observer if this light were not through the haze. So we often refer to the scene radiance J as a haze-free image.

• t is a map called transmission or transparency of the haze. t(x) is a scalar in [0, 1]. Intuitively, $t(x) = 0$ means completely hazy and opaque, $t(x) = 1$ means haze-free and completely clear, and $0 < t(x) < 1$ means semi-transparent.

• A is the atmospheric light. It is a 3D RGB vector usually assumed to be spatially constant. It is often considered as "the color of the atmosphere, horizon, or sky" [49, 18, 79].

The haze is formed by the particles in the atmosphere absorbing and scattering light. The light reflected from an object is partially absorbed by the particles in the atmosphere and is attenuated. The transmission t is the ratio of "the light that is not attenuated and reaches the observer" to "the light reflected from the object". The term $A(1 - t(x))$ is called airlight [40, 18] . The particles scatter the light they absorb, playing as an infinite number of tiny light sources floating in the atmosphere. The airlight is due to these light sources.

Related work:

In computer vision, the methods to handle the ambiguity are roughly in two ways. The first way is to acquire more known variables, reducing the discrepancy between the number of equations and the number of unknowns. In haze removal, this is often by capturing two or more images of the scene. The second way is to use some knowledge or assumptions known beforehand, i.e., priors. The priors impose extra constraints/dependency among the unknown variables.

Single image haze removal methods have to rely on some priors. The priors can be statistical/physical properties, heuristic assumptions, simplifications, and application-based rules. The discrepancy between the number of equations (3N) and the number of unknowns (4N +3) is about N. So the priors are expected to introduce at least one constraint for each pixel.

4. Proposed Work-

In this project, we are implementing two algorithms, to remove the effects of fog and haze by the method of “Dark Channel Prior(DCP)” and “Colour Attenuation Prior(CAP)” respectively.

The dark channel prior is based on the statistics of outdoor haze-free images. We find that, in most of the local regions which do not cover the sky, some pixels (called dark pixels) very often have very low intensity in at least one color (RGB) channel. In hazy images, the intensity of these dark pixels in that channel is mainly contributed by the airlight. Therefore, these dark pixels can directly provide an accurate estimation of the haze transmission. Our approach is physically valid and is able to handle distant objects in heavily hazy images. We do not rely on significant variance of transmission or surface shading. The result contains few halo artifacts. Like any approach using a strong assumption, our approach also has its own limitations. The dark channel prior may be invalid when the scene object is inherently similar to the airlight (e.g., snowy ground or a white wall) over a large local region and no shadow is cast on it. Although our approach works well for most outdoor hazy images, it may fail in some extreme cases. Fortunately, in such situations haze removal is not critical since haze is rarely visible.

The colour attenuation prior is based on the difference between brightness and saturation of pixels within the hazy image. By creating a linear model for the scene depth of the hazy image with a simple but powerful prior and using the learning parameters of a model designed by a supervised learning method, the depth information can be recovered. By means of the depth map obtained by the proposed method, the scene radiance of the hazy image can be recovered easily. Although we have implemented a way to model the scene depth with the brightness and saturation of the hazy image, the dehazing algorithm which is based on the atmospheric scattering model is prone to underestimating the transmission in some cases. To overcome this challenge, some more advanced physical models can be taken into account, which is beyond the scope of this project.

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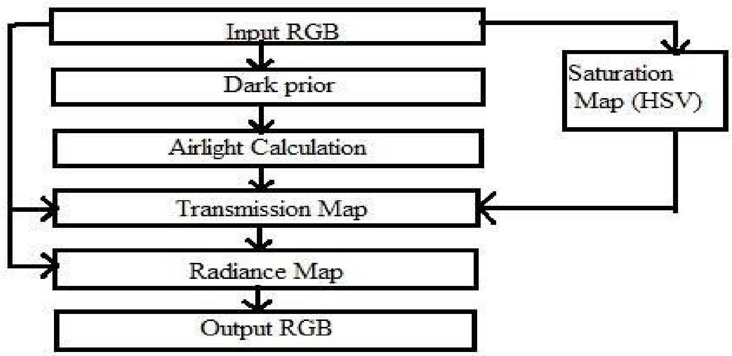
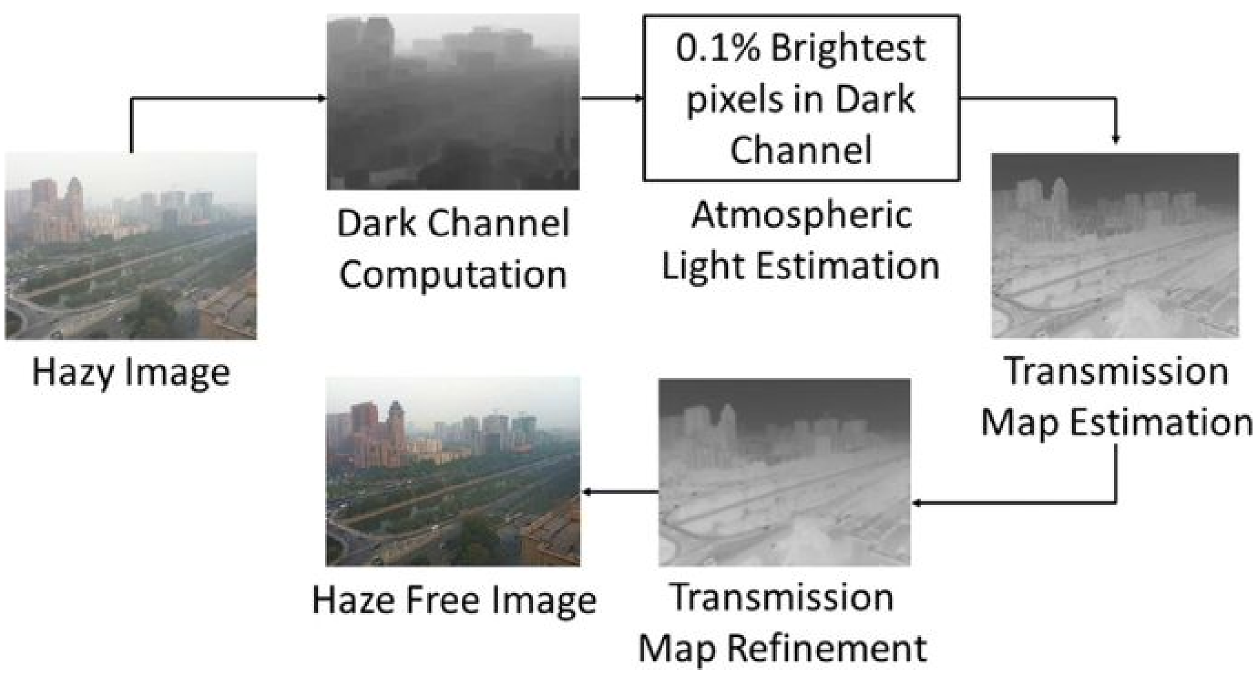
Block Diagram-



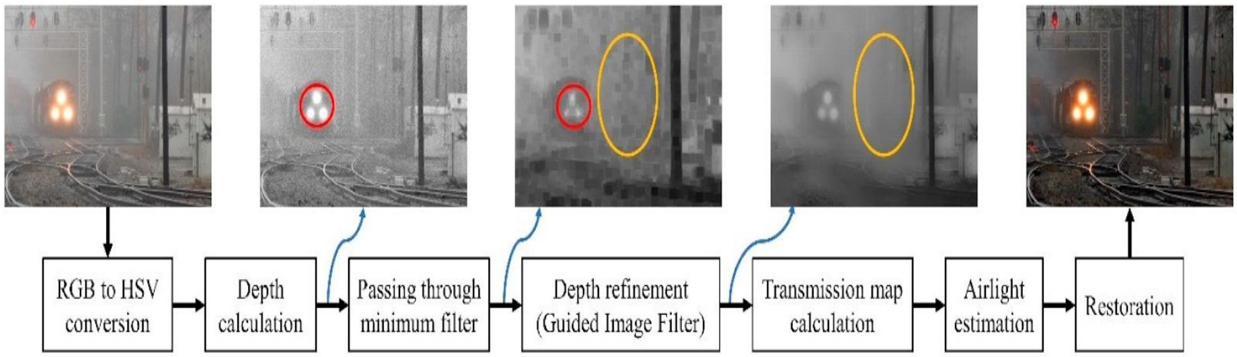
In the DCP method of approach, after importing RGB components of the image, the next step is finding *Dark prior*, and follows through till the output as shown in the diagram.

Using the CAP approach, after importing RGB components of the image, the next step is finding the *Saturation Map*, and then it follows through to finding the *Transmission Map* as shown in the above block diagram.

Architecture of Dark Channel prior-



Architecture for Colour Attenuation Prior-



5. Evaluation and Result Analysis-

Using Dark Channel Prior-

Figs. 1 and 2 show the recovered images and the depth maps. The depth maps are computed and are up to an unknown scaling parameter . The atmospheric lights in these images are automatically estimated (indicated by the red rectangles in Fig. 2). As can be seen, our approach can unveil the details and recover vivid colors even in heavily hazy regions. The estimated depth maps are sharp near the depth edges and consistent with the input images.

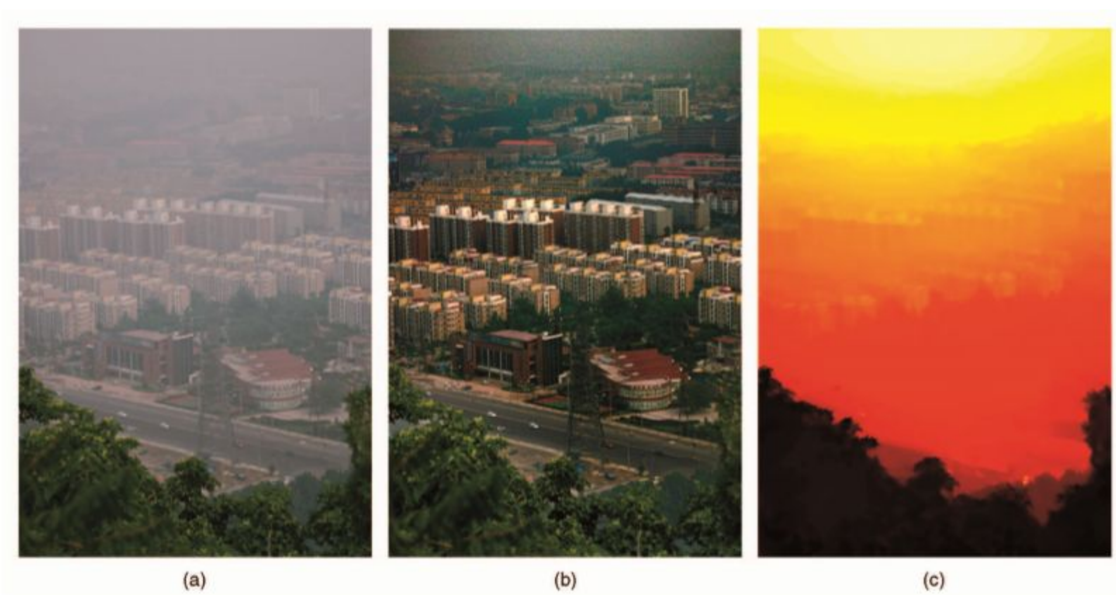


Fig. 1. Haze removal using a single image. (a) Input hazy image. (b) Image after haze removal by our approach. (c) Our recovered depth map.

Fig. 2. Haze removal results. (a) Input hazy images. (b) Restored haze-free images. (c) Depth maps. The red rectangles in the top row indicate where our method automatically obtains the atmospheric light.

Our approach also works for gray-scale images if there are enough shadows. Cityscape images usually satisfy this condition. Fig. 3 shows an example.

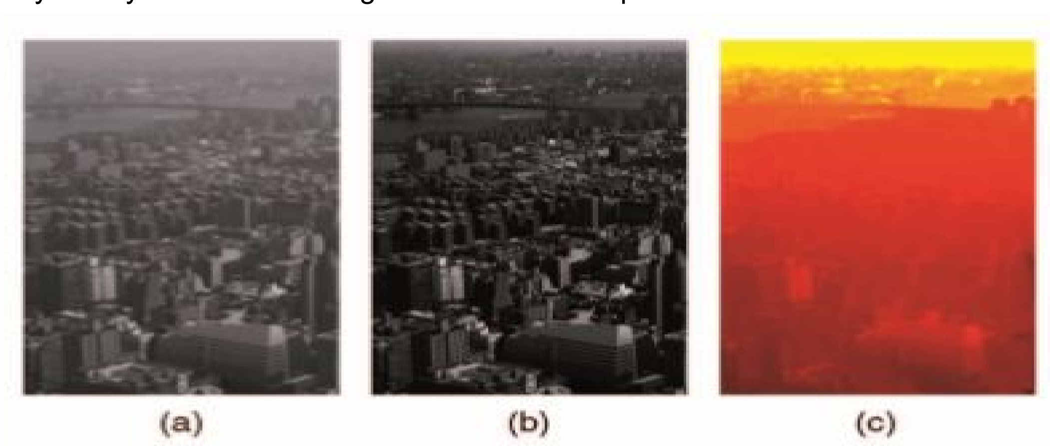


Fig. 3. A gray-scale image example. (a) Input image. (b) Our result. (c) Our recovered depth map.

Using Colour Attenuation Prior-

To detect or remove the haze from a single image is a challenging task in computer vision, because little information about the scene structure is available. In spite of this, the human brain can quickly identify the hazy area from the natural scenery without any additional information. This inspired us to conduct a large number of experiments on various hazy images to find the statistics and seek a new prior for single image dehazing. Interestingly, we find that the brightness and the saturation of pixels in a hazy image vary sharply along with the change of the haze concentration.

Figure 4 gives an example with a natural scene to show how the brightness and the saturation of pixels vary within a hazy image.

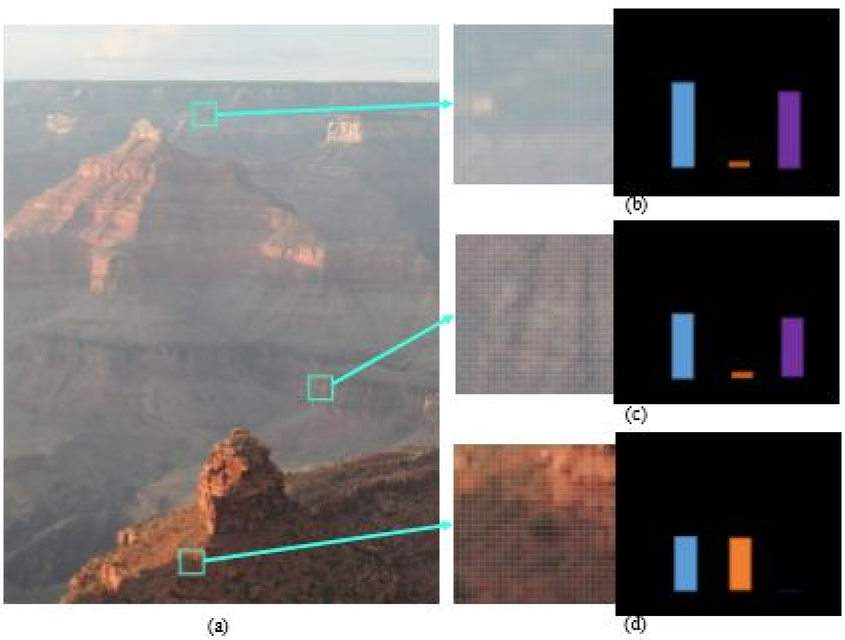


Fig. 4. The concentration of the haze is positively correlated with the difference between the brightness and the saturation. (a) A hazy image. (b) The close-up patch of a dense-haze region and its histogram. (c) The close-up patch of a moderately hazy region and its histogram. (d) The close-up patch of a haze-free region and its histogram.

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

$$d(x) \propto c(x) \propto v(x) - s(x),$$

where d is the scene depth, c is the concentration of the haze, v is the brightness of the scene and s is the saturation. We regard this statistics as color attenuation prior.

As the relationship among the scene depth d, the brightness v and the saturation s has been established and the coefficients have been estimated, we can restore the depth map of a given input hazy. However, this model may fail to work in some particular situations. For instance, the white objects in an image are usually with high values of the brightness and low values of the saturation. Therefore, the proposed model tends to consider the scene objects with white color as being distant. Unfortunately, this misclassification will result in inaccurate estimation of the depth in some cases.

To overcome this problem, we need to consider each pixel in the neighborhood. Based on the assumption that the scene depth is locally constant, we process the raw depth map by:

$$d_r(x) = \min_{y \in \Omega_r(x)} d(y),$$

where Ω(x) is an r x r neighborhood centered at x, and dr is the depth map with scale r. With the estimated depth map, the task of dehazing is no longer difficult.

6. Comparison with Existing Work-

Using Dark Channel Prior-

In Fig.5, we compare our approach with Tan's work . The result of this method has oversaturated colors because maximizing the contrast tends to overestimate the haze layer. Our method recovers the structures without sacrificing the fidelity of the colors (e.g., swan). The halo artifacts are also significantly small in our result.

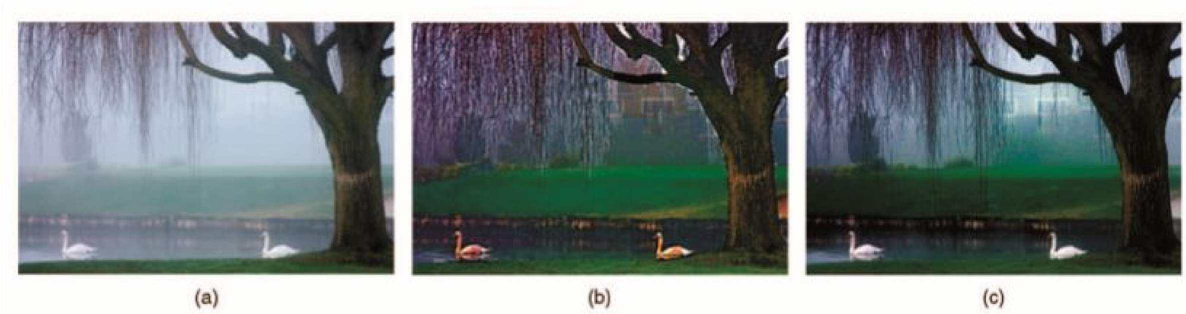


Fig.5. Comparison with Tan's work . (a) Input image. (b) Tan's result. (c) Our result.

Next, we compare our approach with Fattal's work. In Fig. 6, we show that our approach outperforms Fattal's for dense haze. His method is based on local statistics and requires sufficient color information and variance. When the haze is dense, the color is faint and the variance is not high enough for his method to reliably estimate the transmission. Figs. 6b and 6c show his results before and after the MRF extrapolation. Since only parts of transmission can be reliably recovered, even after extrapolation some regions are too dark (mountains) and some hazes are not removed (distant part of the cityscape). Our approach gives natural results in these regions (Fig. 6d).

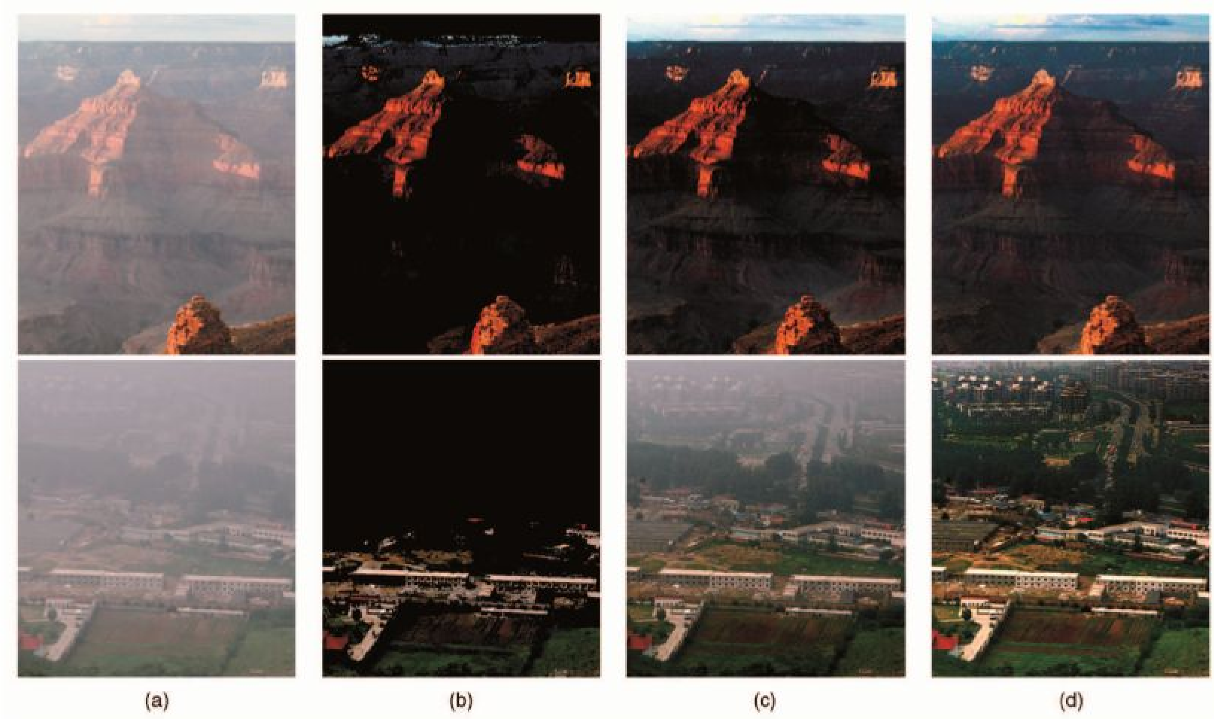


Fig. 6. More comparisons with Fattal's work . (a) Input images. (b) Results before extrapolation, using Fattal's method. The transmission is not estimated in the black regions. (c) Fattal's results after extrapolation. (d) Our results.

But there are also cases where our method fails or is not fully effective. For example-

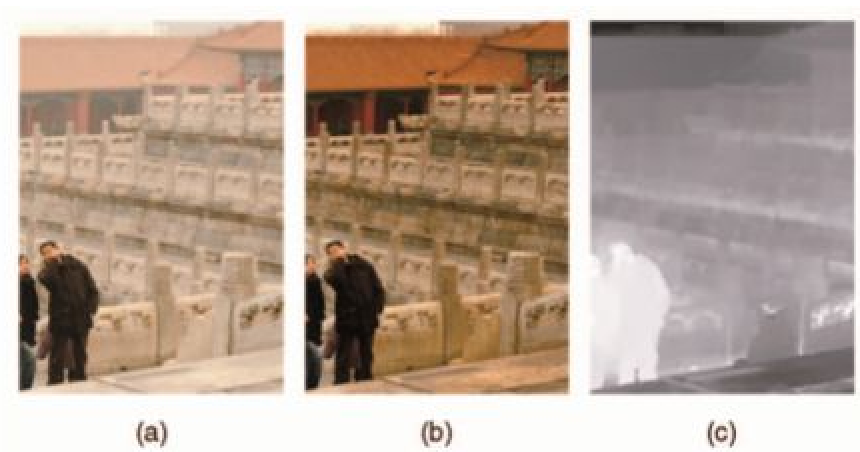


Fig. 7. Failure of the dark channel prior. (a) Input image. (b) Our result. (c) Our transmission map. The transmission of the marble is underestimated.

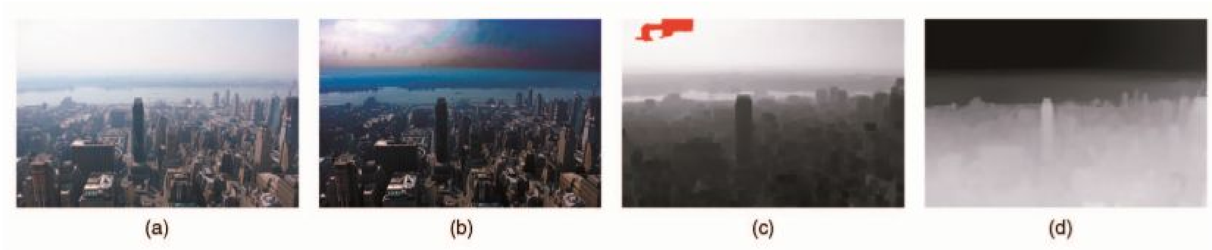


Fig. 8. Failure of the haze imaging model. (a) Input image. (b) Our result. (c) Dark channel. Red pixels indicate where the atmospheric light is estimated. (d) Estimated transmission map.

Using Colour Attenuation Prior-

In order to verify the effectiveness of the proposed dehazing method, we test it on various hazy images and compare with He et al.'s , Tarel et al.'s , Nishino et al.'s and Meng et al.'s methods.

Fig. 9. Qualitative comparison of different methods on real-world images. (a) The hazy images. (b) Tarel et al.'s results. (c) Nishino et al.'s results. (d) He et al.'s results. (e) Meng et al.'s results. (f) Our results.

Figure 9 shows the qualitative comparison of results with the four state-of-the-art dehazing algorithms on challenging real-world images. Figure 9(a) depicts the hazy images to be de-hazed. Figure 9(b-e) shows the results of Tarel et al. , Nishino et al. , He et al. , and Meng et al. , respectively. The results of the proposed algorithm are given in Figure 9(f). As shown in Figure 9(b), most of the haze is removed in Tarel's results, and the details of the scenes and objects are well restored. However, the results significantly suffer from over-enhancement (for instance, the sky region of the first image is much darker than it should be, and the faces of the women in the last image become brown). This is because Tarel's algorithm is based on He et al.'s algorithm which has an inherent problem of overestimating the transmission. Moreover, halo artifacts appear near the discontinuities in Figure 9(b) (see the mountain in the first image and the leaves of the plant in the second image) due to the fact that the "median of the median filter" used is not an edge-preserving filter. The results of Nishino et al. have a similar problem as Nishino et al.'s algorithm tends to over enhance the local contrast of the image. As we can observe in Figure 9(c), the restored images are oversaturated and distorted, especially in the third image (the color of the shirt is changed to dark).

7. Overall Discussion-

In this project, we have implemented a very simple but powerful prior, called the dark channel prior, for single image haze removal. The dark channel prior is based on the statistics of outdoor haze-free images. Combining the prior with the haze imaging model, single image haze removal becomes simpler and more effective.

Since the dark channel prior is a kind of statistics, it may not work for some particular images. When the scene objects are inherently similar to the atmospheric light and no shadow is cast on them (such as the white marble in Fig. 7), the dark channel prior is invalid. The dark channel of the scene radiance has bright values near such objects. As a result, our method will underestimate the transmission of these objects and overestimate the haze layer.

In this project, we have also implemented a novel linear color attenuation prior, based on the difference between the brightness and the saturation of the pixels within the hazy image. By creating a linear model for the scene depth of the hazy image with this simple but powerful prior and learning the parameters of the model using a supervised learning method, the depth information can be well recovered. By means of the depth map obtained by the proposed method, the scene radiance of the hazy image can be recovered easily. Experimental results show that the proposed approach achieves dramatically high efficiency and outstanding dehazing effects as well.

Although we have found a way to model the scene depth with the brightness and the saturation of the hazy image, there is still a common problem to be solved. That is, the scattering coefficient β in the atmospheric scattering model cannot be regarded as a constant in inhomogeneous atmosphere conditions. Therefore, the dehazing algorithms which are based on the atmospheric scattering model are prone to underestimating the transmission in some cases. As almost all the existing single image dehazing algorithms are based on the constant assumption, a more flexible model is highly desired. To overcome this challenge, some more advanced physical models can be taken into account. We leave this problem for our future research.

8. Conclusion-

Fog removal algorithms are becoming more and more useful these days for several processing and vision applications. One of the main problems in processing is the smoke, fog, haze which results in reduction of contrast of the images. Distinction of objects thus becomes complex. Bad weather conditions decrease the operation range of many processes. Combining dark channel prior or color attenuation prior with the degraded image model, haze elimination from a single image becomes more effective and even simpler. Our methods depend upon the haze imaging model, it may fail to work if the model is physically invalid.

In this paper, we proposed an effective algorithm for haze removal focusing on the removal of major demerits remained in previous works. We mainly use the concept of dark channel prior and proposed some set of assumptions to get better results. Also, adaptive result calculation is the main theme of our work. We did simulation, by taking around 50 natural hazy images. On the basis of both subjective and objective measures, our method gives better results compared to some existing methods. In future research work, we may integrate proposed methods in human glasses (while driving) to cope with hazy situations.

This paper introduces an innovative method which used a variant of the dark channel that greatly reduces the recurrent artifacts presented when using the classic dark channel. Analyzing the experimental results of the quantitative analysis performed, it is observed that the proposed algorithm generates competitive results against four state of-the-art algorithms without the need for a refinement stage. Because the proposed method has no refinement stage, additionally, it uses a scaled image to compute the variables t and A which is faster than state-of-the art methods. The computation processing time used by the algorithm makes possible its application in high resolution images and real-time video.

9. References-

[1] Divya Makkar and Mohinder Malhotra, "Single Image Haze Removal Using Dark Channel Prior," International Journal of Engineering and Computer Science (IJECS), vol. 5 no. 1, pp. 15467-15473, (2016).

[2] S. Kim, S. Park, K. Choi, in Korea-Japan Joint Workshop on Frontiers of Computer Vision (FCV), vol. 1. A system architecture for real time traffic monitoring in foggy video, (Mokpo, South Korea, 2015), pp. 1–4. https:// doi.org/10.1109/FCV.2015.7103720.

[3] X. Ji, J. Cheng, J. Bai, T. Zhang, M. Wang, in International Congress on Image and Signal Processing (CISP), vol. 1. Real-time enhancement of the image clarity for traffic video monitoring systems in haze, (Dalian, China, 2014), pp. 11–15. https://doi.org/10.1109/CISP.2014.7003741.

[4] M. Sulami, I. Glatzer, R. Fattal, M. Werman, in IEEE International Conference on Computational Photography (ICCP). Automatic recovery of the atmospheric light in hazy images, vol. 1, (Santa Clara, USA, 2014), pp. 1–11. https://doi.org/10.1109/ICCPHOT.2014.6831817

[5] W. Ren, S. Liu, H. Zhang, J. Pan, X. Cao, M.-H. Yang, in Computer Vision – ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part II, ed. by B. Leibe, J. Matas, N. Sebe, and M. Welling. Single image dehazing via multi-scale convolutional neural networks (Springer, Cham, 2016), pp. 154–169. https://doi.org/10.1007/ 978-3-319-46475-6_10

[6 . Q. Zhu, J. Mai, L. Shao, A fast single image haze removal algorithm using color attenuation prior. IEEE Trans. Image Process. 24(11), 3522–3533 (2015). https://doi.org/10.1109/TIP.2015.2446191

[7] V. Sahu, M. M. S. Vinkey Sahu, A survey paper on single image dehazing. Int. J. Recent Innov. Trends Comput. Commun. (IJRITCC). 3(2), 85–88 (2015)

[8] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in CVPR, 2016

18BCE2354

[9] Experimental images, available online: http://johanneskopf.de/publications/deep_photo/dehazing/index.html

18BCE2356

[10] Experimental images, available online: http://kaiminghe.com/cvpr09/comparisons.html

[11] B. Li, X. Peng, Z. Wang, J. Xu, and D. Feng, "Aod-net: All-in-one dehazing network," in ICCV, 2017.

[12] Z. Xu, X. Yang, X. Li, X. Sun, and P. Harbin, "Strong baseline for single image dehazing with deep features and instance normalization," BMVC, 2018.

[13] B. Li, W. Ren, D. Fu, D. Tao, D. Feng, W. Zeng, and Z. Wang, "Reside: A benchmark for single image dehazing," arXiv preprint arXiv:1712.04143, 2017.

[14] B. Cai, X. Xu, K. Jia, C. Qing, and D. Tao, "Dehazenet: An end-to-end system for single image haze removal," TIP, vol. 25, no. 11, pp. 5187– 5198, 2016.

[15] W. Ren, L. Ma, J. Zhang, J. Pan, X. Cao, W. Liu, and M.-H. Yang, "Gated fusion network for single image dehazing," CVPR, 2018.

Appendix for Acronyms-

DCP	Dark Channel Prior
CAP	Colour Attenuation Prior
ML	Machine learning

Appendix for Individual Contribution in group-

Sr.No	Reg.No	Role and Responsibility	Digital Signature
1	18BCE2354	Implementation of DCP, report making	Prajeeth kumar M.J
2	18BCE2356	Implementation of CAP, report making	Sumanth krishna
3	18BCE2366	Implementation of CAP, report making	Shreya Chaudhary
4	18BCE2399	Implementation of DCP, report making	Shravan.A.J