

PRIOR-BASED OPTIMIZATION APPROACHES FOR SINGLE IMAGE DEHAZING

Sidharth Gautam



**Department Of Electrical Engineering
INDIAN INSTITUTE OF TECHNOLOGY DELHI**

August 2022

PRIOR-BASED OPTIMIZATION APPROACHES FOR SINGLE IMAGE DEHAZING

A THESIS

submitted by

Sidharth Gautam
2015EEZ8415

*in partial fulfilment of the requirements
for the award of the degree of*

of

Doctor of Philosophy



Department Of Electrical Engineering
INDIAN INSTITUTE OF TECHNOLOGY DELHI

August 2022

THESIS CERTIFICATE

This is to certify that the thesis titled **Prior-based Optimization Approaches for Single Image Dehazing**, submitted by **Sidharth Gautam**, to the Indian Institute of Technology, Delhi, for the fulfillment of the requirements for the award of the degree of **Doctor of Philosophy**, is a bonafide record of the research work done by him under our supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.



Dr. Bijaya Ketan Panigrahi (Supervisor)
Professor, Dept. of Electrical Engineering
Indian Institute of Technology Delhi
Hauz Khas, New Delhi, Delhi 110016



Dr. Tapan Gandhi (Supervisor)
Professor, Dept. of Electrical Engineering
Indian Institute of Technology Delhi
Hauz Khas, New Delhi, Delhi 110016

Place: IIT, New Delhi
Date: August 22, 2022

ACKNOWLEDGEMENTS

During the research period, I was inspired by many people and felt grateful to them. This page is dedicated to all those who have made such memorable contributions to my study and life.

To start with, first of all, I would like to give sincere thanks and gratitude to my esteemed Supervisors, Prof. B. K. Panigrahi (Professor, Department of Electrical Engineering, Indian Institute of Technology Delhi) and Prof. Tapan Kumar Gandhi (Associate Professor, Department of Electrical Engineering, Indian Institute of Technology Delhi), for the invaluable guidance, motivation, and continuous support throughout the research work. Their inspiring discussions, friendly cooperation, and suggestions throughout the work guided me with an impetus to work. I am indeed fortunate to have such a lovely, warm, and cooperative advisor. I owe them everything I have learned during my research work, be it developing an aptitude for thinking like a research scholar or critically reading and analyzing. I had shortcomings; still, they showed confidence in my abilities. I learned how to keep working with patience and perseverance in the face of failures. Most importantly, I learned that there are no shortcuts to success; one must work hard. And in this journey, I also evolved as a better human being.

Further, I would like to thank my Doctoral Committee Members: Dr Sumantra Dutta Roy (Associate Professor, Department of Electrical Engineering, Indian Institute of Technology Delhi), Dr Anup Singh (Associate Professor, Centre for Biomedical Engineering, Indian Institute of Technology Delhi) and Dr Brejesh Lal (Professor, Department of Electrical Engineering, Indian Institute of Technology Delhi) for their constructive feedback's, helpful suggestions and profound evaluation on many of my research presentations. The office staff of the Dept. of Electrical Engineering, IIT Delhi, has been a great help. My sincere thanks to them as well.

I am grateful to IIT Delhi's Multimedia lab and Neurocomputing Lab for providing the workspace and other research-related resources. I am also thankful to the Ministry of Human Resource and Development (MHRD), Government of India, for awarding me with a research scholarship. I would like to appreciate the Finance Department of IIT Delhi for the timely and quick disbursement of the fellowship. I'd also want to thank the open-source software LATEX and Ubuntu for making this thesis feasible in such a short period.

I was also fortunate to obtain advice from and collaborate with several prominent researchers in IIT-Delhi. I sincerely wish to thank Nitin Kumar, a research scholar in the Dept. of Mathematics, who collaborated with me to give a mathematical form to my research ideas over the past two years. Now is a time to acknowledge those excellent people who have contributed significantly to my thesis. They stood with me during my difficult times and provided me with unwavering support in various roles. I'd want to convey my heartfelt gratitude to my buddy Anirudra Diwakar,

who never hesitated to listen and understand my problems and consistently pushed me to discover answers throughout the research process. I am also thankful to my friends, Mr Debanjan Konar and Mr Rajiv Verma, who supported me throughout the research.

Finally, my experience at IIT-Delhi could never be as enriching and entertaining without my friends - Sneha Sehrawat, Harikesh Dalal, Rahul Jaiswal, and Aakash. Your friendship and experiences kept me motivated, and the leisure time activities with you kept me in a good mood. Thank you for your precious company.

The list goes on, and it is difficult to mention each name here, for whom I feel a sense of gratitude. My apologies to those whose names could not be mentioned here.

Finally, I would like to thank my family, whom I owe greatly. I am forever indebted to my grandfather and parents for their sacrifices, endless love, and for giving me strength and opportunities to explore new directions in life and shape my career. Your prayer for me was what sustained me thus far through all the difficulties. Many thanks to my wonderful brothers Suraj and Sunny for always being with me through my ups and downs. I also like to thank my in-laws for their support and encouragement to finish this work. Lastly, I would like to thank my lovely wife Annu and beloved daughter Sia. Their unparalleled love, understanding, patience, and tolerance over the last years have been the most potent energy source that has propelled me forward despite the challenges. They never complained about my absence or anything else, which gave me peace of mind to focus on my work. This journey would not have been easier without their love and support, and I dedicate this milestone to all of you. Besides, I want to leave some space in the loving memory of my younger sister Late Shabnam, who wished to see me conferred with this title.



Sidharth Gautam

ABSTRACT

A hazy environment obscures visibility and hinders the performance of many computer vision tasks. The process of removing haze using a single image and compensating for the attenuated radiance is known as *single image dehazing*. Retrieving haze-free results using a single image is an ill-posed and under-constrained problem due to the lack of information such as the transmittance-map (i.e., T -map) and the global air-light vector (A_∞). This research aims to develop *novel priors and boundary constraints using statistical/physical properties or heuristic assumptions to forecast the unknown information required for dehazing*. To this aim, we propose dehazing techniques for restoring visibility in aerial, terrestrial, and underwater imaging under diverse illumination and haze conditions. We begin with an introduction to the dehazing problem and provide a literature review of the related works to investigate the challenges and the ambiguities associated with haze-free image retrieval. Unmanned Aerial Vehicle (UAV) based imagery provides a valuable source of information for both the consumer and computational photographers. But unfortunately, these images are often obfuscated by many factors such as clouds occlusion, poor atmospheric illumination, unpleasant weather conditions, and the limited imaging capability of the UAVs. To retrieve the visibility in aerial imaging, a model-based dehazing scheme using radiance *boundary constraint and graph model* has been proposed. In dehazing, the over-estimation of air-light causes darker and visually unpleasant results, while its under-estimation destroys subtle details from the bright regions such as the sky. Therefore, the accurate estimation of the global air-light to approximate the haze thickness is critical for improving the micro-level visibility. For advanced dehazing performance, a novel statistical prior called *color constancy prior (i.e., CCP)* has been proposed to improve the robustness of air-light estimation under varicolored illumination. Furthermore, adapting the local-patch under different hazy conditions is considered an open research problem in dehazing. To resolve this, a novel self-adaptive prior named *weighted median channel prior (i.e., WMCP)* has been proposed that works by leveraging the spatially changing haze statistics and selecting the optimal local-patch corresponding to the haze density of the input image, which conventional methods frequently fail to do. In addition, a follow-up technique called *Edge Modulation*, has been proposed to repair details lost due to haze. Many image priors and assumptions used in the conventional dehazing frameworks have significant inconveniences as they impose hard bounding constraints for the problem's solution and may not always produce distortion-free results under varying haze conditions. To tackle this, an iterative optimization approach is proposed to effectively estimate & regularize the T -map. The utility of the proposed methodology is to solve the dark channel's hard zeroing constraint without brute-forcing a highly non-convex equation by introducing a novel energy function that stabilizes the process of T -map estimation in haze images. Extensive experimental results on both real and synthetic haze datasets demonstrate the dehazing efficacy of the proposed method with many other progressive techniques.

सार

एक धुंधला वातावरण दृश्यता को अस्पष्ट करता है और कंप्यूटर विज्ञान से संबंधित कार्यों के प्रदर्शन में बाधा डालता है। एकल छवि का उपयोग कर धुंध को हटाने और क्षीण हुई दृश्य चमक को पुनः प्राप्त करने की प्रक्रिया को Single Image Dehazing कहा जाता है। Dehazing के लिए उपयुक्त कारक जैसे संचरण-मैप (अथार्थ, T-मैप) और वैश्विक वायु-प्रकाश (A_∞) को एकल छवि का उपयोग करके धुंध-मुक्त परिणाम प्राप्त करने के लिए अनुमानित करना एक गंभीर समस्या है। इस शोध का उद्देश्य dehazing के लिए आवश्यक अज्ञात कारकों का पूर्वानुमान लगाने के लिए सांख्यिकीय/भौतिक गुणों या मान्यताओं का उपयोग करके नए prior और boundary constraints को विकसित करना है। इस उद्देश्य के लिए, हम विविध रोशनी और धुंध की स्थिति के तहत हवाई, स्थलीय और पानी के नीचे इमेजिंग में दृश्यता बहाल करने के लिए डीहेजिंग तकनीकों का प्रस्ताव करते हैं। हम एकल छवियों में धुंध समस्या के परिचय के साथ शुरू करते हैं और धुंध-मुक्त छवि पुनर्प्राप्ति से जुड़ी चुनौतियों और अस्पष्टताओं की जांच के लिए संबंधित कार्यों की एक साहित्य समीक्षा प्रदान करते हैं। मानव रहित हवाई वाहन (यानी, यूएवी) आधारित इमेजरी उपभोक्ता और कम्प्यूटेशनल फोटोग्राफर दोनों के लिए सूचना का एक मूल्यवान स्रोत प्रदान करती है। लेकिन दुर्भाग्य से, इन छवियों को अक्सर कई कारकों से बाधित किया जाता है जैसे कि बादलों का आना, खराब वायुमंडलीय रोशनी, अप्रिय मौसम की स्थिति और यूएवी की सीमित इमेजिंग क्षमता। हवाई इमेजिंग में दृश्यता को पुनः प्राप्त करने के लिए Boundary Constraint and Graph Model का उपयोग करके एक dehazing तकनीक प्रस्तावित की गई है। Dehazing में, वैश्विक वायु-प्रकाश का अधिक अनुमान गहरा और अप्रिय परिणाम देता है, जबकि इसका कम आकलन आकाश जैसे उज्ज्वल क्षेत्रों से सूक्ष्म विवरण को नष्ट कर देता है। इसलिए, धुंध की मोटाई का अनुमान लगाने के लिए वैश्विक वायु-प्रकाश का सटीक अनुमान सूक्ष्म स्तर की दृश्यता में सुधार के लिए महत्वपूर्ण है। उन्नत डीहेजिंग प्रदर्शन के लिए, एक नया सांख्यिकीय जिसे color constancy prior (यानी, CCP)} कहा जाता है, को विविध रोशनी के तहत वायु-प्रकाश अनुमान की मजबूती में सुधार करने के लिए प्रस्तावित किया गया है। इसके अलावा, अलग-अलग धुंध परिस्थितियों में स्थानीय-पैच को T-मैप और एयर-लाइट को अनुमानित करने के लिए अनुकूलित करना भी डीहेजिंग में एक शोध समस्या माना है। इसे हल करने के लिए, weighted median channel prior (यानी, WMCP)} नामक एक स्व-अनुकूली तकनीक प्रस्तावित की गई है जो स्थानिक रूप से बदलते धुंध के आंकड़ों का लाभ उठाकर काम करती है और इनपुट छवि के धुंध घनत्व के अनुरूप इष्टतम स्थानीय-पैच का चयन करती है, जो पारंपरिक तरीके अक्सर करने में विफल होते हैं। इसके अलावा, धुंध के कारण खोए हुए विवरणों की मरम्मत के लिए edge modulation नामक एक अनुवर्ती तकनीक का प्रस्ताव किया गया है। पारंपरिक डीहेजिंग फ्रेमवर्क में उपयोग किए जाने वाले कई priors and assumptions में महत्वपूर्ण असुविधाएँ होती हैं क्योंकि वे समस्या के समाधान के लिए कठोर बाध्यताएँ लगाते हैं और अलग-अलग धुंध स्थितियों के तहत हमेशा विरूपण-मुक्त परिणाम उत्पन्न नहीं कर सकते हैं। इससे निपटने के लिए, T-मैप को प्रभावी ढंग से नियमित करने के लिए एक पुनरावृत्त अनुकूलन दृष्टिकोण का प्रस्ताव है। प्रस्तावित कार्यप्रणाली की उपयोगिता एक novel energy फंक्शन को पेश करके non-convex equation को मजबूर किए बिना dark channel की हार्ड शून्यिंग बाधा को हल करना है जो धुंध छवियों में T-मैप अनुमान की प्रक्रिया को स्थिर करता है। वास्तविक और सिंथेटिक धुंध डेटासेट दोनों पर व्यापक प्रयोगात्मक परिणाम कई अन्य प्रगतिशील तकनीकों के साथ प्रस्तावित विधि की dehazing प्रभावकारिता को प्रदर्शित करते हैं।

Contents

ACKNOWLEDGEMENTS	i
ABSTRACT	iii
LIST OF TABLES	vii
LIST OF FIGURES	xii
ABBREVIATIONS	xiii
NOTATION	xiv
1 Introduction	1
1.1 Background	1
1.2 Motivation	15
1.3 Objective of the Thesis	16
2 A Model-based dehazing scheme for unmanned aerial vehicle system using radiance boundary constraint and graph model	17
2.1 Introduction	17
2.2 Proposed Methodology	17
2.2.1 Air-light Estimation	17
2.2.2 Boundary constraint for Transmission-map Estimation	18
2.2.3 Graph model for Transmission-map refinement	21
2.2.4 Haze-free image retrieval using color correction	23
2.3 Evaluation and Results	25
2.3.1 Evaluation on real datasets	26
2.3.2 Evaluation on synthetic datasets	28
2.4 Discussion	31
2.5 Conclusion	31

3	An Improved Air-Light Estimation Scheme for Single Haze Images Using Color Constancy Prior	33
3.1	Introduction	33
3.2	Background	33
3.3	Color Constancy Prior	36
3.4	Evaluation and Results	38
3.5	Conclusion	40
4	WMCP-EM: A Multi-model Dehazer for visibility restoration in single images	41
4.1	Introduction	41
4.2	Proposed methodology	41
4.2.1	Weighted median channel prior (WMCP)	41
4.2.2	Edge modulation	45
4.3	Evaluation and Results	46
4.3.1	Evaluation on real datasets	48
4.3.2	Evaluation on synthetic datasets	48
4.4	Ablation Study	54
4.5	Conclusion	55
5	A Dark Channel inspired Iterative Optimization for Single Image Dehazing	56
5.1	Introduction	56
5.2	Proposed methodology	56
5.2.1	Efficient Estimation of transmission-map	56
5.3	Evaluation and Results	59
5.3.1	Evaluation on Real Datasets	59
5.3.2	Evaluation on Synthetic Datasets	61
5.4	Ablation Study	65
5.5	Conclusion	65
6	Summary and Conclusion	67
6.1	Contributions of the Thesis	68
6.2	Future Research Directions	69

A	Appendix	70
B	Performance Measures	74
B.0.1	Mean square error (MSE)	74
B.0.2	Peak signal to noise ratio (PSNR)	74
B.0.3	PSNR-HVS-M	75
B.0.4	Structural similarity index measure (SSIM)	75
B.0.5	Feature similarity index measure (FSIM)	76

List of Tables

2.1	Quantitative comparison using FR-IQA metrics on synthetic Reside- β data-set with different haze level.	30
2.2	Average run-time comparison with other state-of-the-art methods.	30
4.1	Quantitative comparison on synthetic Reside SOTS-I data-set with different haze level.	53
4.2	Quantitative comparison on synthetic outdoor haze data-set with fixed haze level.	53
4.3	Quantitative performance of the ablation experiments evaluated on synthetic data-set.	55
5.1	Average FR-IQA score.	64
5.2	Quantitatively Performance of the Ablation Experiments Evaluated Synthetic dataset [1].	64

List of Figures

1.1	<i>A pictorial description of the haze imaging model. Image formation in inclement weather conditions, where air-light is directed directly and indirectly towards the camera after reflection from an object’s surface.</i>	2
1.2	<i>The process of dehazing. (a) Input haze image $I(\mathbf{x})$. (b) Estimated air-light A_∞, which roughly approximate the haze density. (c) Estimated $T(\mathbf{x})$, which is closely related to the scene-depths of (a). (d) The dehazed output generated by using Eq. (2.3)</i>	4
1.3	<i>An illustration of brute-forcing hard zeroing constraint on dehazing using DCP-based techniques. (a) A real-world hazy picture. (b)-(d) Haze-free images recovered by He <i>et al.</i> [2], Yang <i>et al.</i> [3] and our proposed methodology, respectively. (e)-(f) Transmission maps corresponding to (b)-(c) using Eq. (1.12) (Best viewed on zoom-in).</i>	8
1.4	<i>Taxonomy of single image dehazing methods.</i>	9
2.1	<i>An example to illustrate the global air-light estimation. (a) Real UAVs haze images. (b) Corresponding Dark channels. (c) Top 0.1% of brightest pixels in the dark channel. (d) Top 0.1% of brightest pixels is used a mask to find out the threshold Δ. (e) Logical AND of (c)-(d) images to identify most haze-opaque pixels. (f) Pixels mapped to the input image for air-light estimation. (g) Estimated air-light.</i>	19
2.2	<i>Illustration of the effect of patch variation while estimating the transmission-map for haze images. (a) UAVs haze image (top) and terrestrial haze image (bottom). The transmission-map derived by Eq. (2.6) with the patch size of (b) $\Omega=5$ (c) $\Omega=11$ (d) $\Omega=15$ (e) $\Omega=21$.</i>	20
2.3	<i>Illustration of transmission-map refinement using the graph model. (a) Tri-map replica. (b) Graph model before optimization. (c) Graph model after optimization. (d) Filtered tri-map replica.</i>	21
2.4	<i>An example of transmission-map refinement and radiance recovery using the proposed approach. (a) and (c) Filtered transmission map derived from images shown in Fig. 2.2(d). (b) and (d) Final dehazing results.</i>	22
2.5	<i>Statistical difference between a terrestrial image and UAVs image. Top row: Terrestrial image dataset [4], [5] and its histogram. Bottom row: UAVs image dataset [6], [7] and its histogram.</i>	24

2.6	<i>Qualitative comparison with other state-of-the-art methods on QUICK BIRD dataset [8]. (a) Satellite haze images. (b) Fu et al. [9] (c) Kwok et al. [10] (d) He et al. [2] (e) Zhu et al. [11] (f) Meng et al. [12] (g) Cai et al. [13] (h) Zhang et al. [14] (i) Yang et al. [3] (j) Proposed method (Please zoom-in for better illustration of minor details).</i>	26
2.7	<i>Qualitative comparison with other state-of-the-art methods on PLEIADES dataset [15]. (a) Satellite haze images. (b) Fu et al. [9] (c) Kwok et al. [10] (d) He et al. [2] (e) Zhu et al. [11] (f) Meng et al. [12] (g) Cai et al. [13] (h) Zhang et al. [14] (i) Yang et al. [3] (j) Proposed method (Please zoom-in for better illustration of minor details).</i>	26
2.8	<i>Qualitative comparison with other state-of-the-art methods on USC-SIPI dataset [16] (a) Satellite haze images. (b) Fu et al. [9] (c) Kwok et al. [10] (d) He et al. [2] (e) Zhu et al. [11] (f) Meng et al. [12] (g) Cai et al. [13] (h) Zhang et al. [14] (i) Yang et al. [3] (j) Proposed method (Please zoom-in for better illustration of minor details).</i>	27
2.9	<i>Qualitative comparison with other state-of-the-art methods on RESIDE-β dataset [1]. (a) Synthetic haze images. (b) Fu et al. [9] (c) Kwok et al. [10] (d) He et al. [2] (e) Zhu et al. [11] (f) Meng et al. [12] (g) Cai et al. [13] (h) Zhang et al. [14] (i) Yang et al. [3] (j) Proposed method (k) Ground truth (Please zoom-in for better illustration of minor details in the marked region).</i>	29
2.10	<i>Failure examples of the proposed method.(a) and (b) Input image. (c) and (d) Output image.</i>	31
3.1	<i>Significance of estimation of air-light (A_∞) in the dehazing framework. (a) Real haze image, (b) Impact of over-estimated A_∞ by He et al. [2], (c) Impact of under-estimated A_∞ impact by Berman et al. [17], (d) Impact of wrong-estimated A_∞ impact, (e) Impact of Accurately estimated A_∞ by our method.</i>	34
3.2	<i>Pictorial illustrations to represent the haze impacts in different regions of an image. (a) Original haze images with manually identified light-haze, medium-haze, and dense-haze regions [18]. (b) Average histogram of all haze-regions. (c) The air-light profile along the scene-depth (Note: the brightness mean in Fig. 3.2(b) is generated from 4000 manually extracted 71×71 close-up patches, whereas in Fig. 3.2(c) the air-light profile is generated from 400 real haze images).</i>	37
3.3	<i>An example of global air-light (A_∞) estimation with other state-of-the-art methods. (a) Real haze images. (b) The air-light (A_∞) pixel clusters, where each color represents A_∞ estimated by different methods. (c) The air-light (A_∞) color estimated by He et al. [2], Meng et al. [12], Bahat et al. [19], Berman et al. [17] and ours along with manually identified GT.</i>	39
3.4	<i>Accuracy evaluation of global air-light (A_∞) estimation in terms of L2-norm.</i>	39

3.5	Qualitative comparison of dehazing results with other state-of-the-art methods. (a) Real haze Image with scenery object brighter than the air-light (A_∞). The scene-radiance $J(\mathbf{x})$ obtained by (b) He <i>et al.</i> [2], (c) Zhu <i>et al.</i> [11], (d) Meng <i>et al.</i> [12], (e) Cai <i>et al.</i> [13], (f) Berman <i>et al.</i> [17], (g) Dhara <i>et al.</i> [20], (h) Ours. (<i>Best viewed with zoom-in</i>).	39
4.1	<i>An integrated proposed dehazing framework. The architecture consists of multiple stages. First of all, the scene-depth $d(x)$ has been estimated using the proposed weighted median channel prior (WMCP), followed by the transmission-map $T^*(x)$ refinement using a guided image filter (GIF) [21]. Secondly, the global air-light (A_∞) vector estimated by color constancy prior [22] has been used to recover the scene radiance $J(x)$. Finally, an edge emphasizing modulation transfer function is developed to repair the faint details in $J(x)$ and to obtain the true scene radiance $J_e(x)$.</i>	42
4.2	<i>Illustration of haze-statistics on RESIDE * dataset [1]. (a) Input images corresponding to the variable haze thickness plotted on a β scale. (b) PSNR variation with respect to local-patch (Ω). (c) Impacts of haze density on the standard deviation (σ). (Note: * represents manually identified 2700 images from RESIDE dataset [1], where haze-images corresponding to brighten scenery objects are filtered out to analyze the dehazing efficacy on the true colors of the scene in Fig. 4.2(b). In addition, the entire RESIDE dataset [1] of 13990 images has been used in Fig. 4.2(c) to analyze the impacts of haze-density on the average score (σ).</i>	43
4.3	<i>Example of scene-depth $d(x)$ estimation and transmission-map $T^*(x)$ estimation for haze image $I(x)$ using weighted median channel prior (WMCP).</i>	45
4.4	Impact of edge modulated unsharp masking to the dehazing results. (a) Real haze images $I(x)$. (b) Dehazed image $J(x)$. (c) Restored scene-radiance $J_e(\mathbf{x})$. (<i>Best viewed with zoom-in</i>).	47
4.5	Qualitative comparison of dehazing results with many other progressive techniques. (a) Real haze Image. The scene-radiance, corresponding transmission-map and air-light obtained by (b) He <i>et al.</i> [2] (c) Gibson <i>et al.</i> [23] (d) Zhu <i>et al.</i> [11] (e) Meng <i>et al.</i> [12] (f) Cai <i>et al.</i> [13] (g) Chen <i>et al.</i> [24] (h) Ren <i>et al.</i> [25] (i) Li <i>et al.</i> [26] (j) Ours. (<i>Note: Li et al. [26] re-formulated Eq. (1.3) to avoid T-map estimation by integrating A_∞ and T into one parameter</i>).	49
4.6	Qualitative comparison of dehazing results with many other progressive techniques. (a) Real haze Image. The scene-radiance, corresponding transmission-map and air-light obtained by (b) He <i>et al.</i> [2] (c) Gibson <i>et al.</i> [23] (d) Zhu <i>et al.</i> [11] (e) Meng <i>et al.</i> [12] (f) Cai <i>et al.</i> [13] (g) Chen <i>et al.</i> [24] (h) Ren <i>et al.</i> [25] (i) Li <i>et al.</i> [26] (j) Ours. (<i>Note: Li et al. [26] re-formulated Eq. (1.3) to avoid T-map estimation by integrating A_∞ and T into one parameter</i>).	49
4.7	Qualitative comparison of dehazing results with many other progressive techniques. (a) Real haze Image with scenery objects brighter than the air-light (A_∞). The scene-radiance obtained by (b) He <i>et al.</i> [2] (c) Gibson <i>et al.</i> [23] (d) Zhu <i>et al.</i> [11] (e) Meng <i>et al.</i> [12] (f) Cai <i>et al.</i> [13] (g) Chen <i>et al.</i> [24] (h) Ren <i>et al.</i> [25] (i) Li <i>et al.</i> [26] (j) Ours. (<i>Best viewed with zoom-in</i>).	49

4.8	Qualitative comparison of dehazing results with many other progressive techniques on RESIDE SOTS-Indoor dataset [1]. (a) Synthetic haze Images. (b) He <i>et al.</i> [2] (c) Gibson <i>et al.</i> [23] (d) Zhu <i>et al.</i> [11] (e) Meng <i>et al.</i> [12] (f) Cai <i>et al.</i> [13] (g) Chen <i>et al.</i> [24] (h) Ren <i>et al.</i> [25] (i) Li <i>et al.</i> [26] (j) Ours (k) GT. (<i>Best viewed with zoom-in</i>).	50
4.9	Qualitative comparison of dehazing results with many other progressive techniques on RESIDE SOTS-Outdoor dataset [1]. (a) Synthetic haze Images. (b) He <i>et al.</i> [2] (c) Gibson <i>et al.</i> [23] (d) Zhu <i>et al.</i> [11] (e) Meng <i>et al.</i> [12] (f) Cai <i>et al.</i> [13] (g) Chen <i>et al.</i> [24] (h) Ren <i>et al.</i> [25] (i) Li <i>et al.</i> [26] (j) Ours (k) GT. (<i>Best viewed with zoom-in</i>).	50
4.10	Qualitative comparison of dehazing results with many other progressive techniques on NTIRE dataset [27]. (a) Synthetic haze Images. (b) He <i>et al.</i> [2] (c) Gibson <i>et al.</i> [23] (d) Zhu <i>et al.</i> [11] (e) Meng <i>et al.</i> [12] (f) Cai <i>et al.</i> [13] (g) Chen <i>et al.</i> [24] (h) Ren <i>et al.</i> [25] (i) Li <i>et al.</i> [26] (j) Ours (k) GT. (<i>Best viewed with zoom-in</i>).	51
4.11	Qualitative comparison of dehazing results with many other progressive techniques on FRIDA dataset [28]. (a) Synthetic haze Images. (b) He <i>et al.</i> [2] (c) Gibson <i>et al.</i> [23] (d) Zhu <i>et al.</i> [11] (e) Meng <i>et al.</i> [12] (f) Cai <i>et al.</i> [13] (g) Chen <i>et al.</i> [24] (h) Ren <i>et al.</i> [25] (i) Li <i>et al.</i> [26] (j) Ours (k) GT. (<i>Best viewed with zoom-in</i>).	51
4.12	Quantitative comparison of visible edge difference (E_d) with other state-of-the-art methods.	53
4.13	Ablation study qualitative results on the synthetic RESIDE SOTS-Outdoor dataset[1]. (a) Haze image. (b) Case-1 (c) Case-2 (d) Case-3 (e) Case-4 (f) Case-5 (g) Case-6 (<i>Best viewed with zoom-in</i>).	55
5.1	Suggested architecture of the dehazing algorithm.	57
5.2	Qualitative comparison with other progressive techniques on real-world images. (a) A real-world hazy picture. (b)-(g) Haze-free image and Transmission-map recovered by He <i>et al.</i> [2], Zhu <i>et al.</i> [11], Yang <i>et al.</i> [3], Ju <i>et al.</i> [29], Gautam <i>et al.</i> [C4], and our proposed method, respectively. (<i>Note: Li et al. [26] and Qu et al. [30] eliminated the T-map estimation by combining A_∞ and T into a single parameter</i>).	61
5.3	Qualitative dehazing comparison with other progressive techniques on real-world images. (a) Haze Images. (b) He <i>et al.</i> [2] (c) Zhu <i>et al.</i> [11] (d) Li <i>et al.</i> [26] (e) Yang <i>et al.</i> [3] (f) Qu <i>et al.</i> [30] (g) kim <i>et al.</i> [31] (h) Dhara <i>et al.</i> [20] (i) Ju <i>et al.</i> [29] (J) Gautam <i>et al.</i> [C4] (k) Ours. (<i>Best viewed on zoom-in</i>).	61
5.4	Qualitative dehazing comparison with other progressive techniques on RESIDE- β SOTS dataset [1]. (a) Synthetic haze image. (b) He <i>et al.</i> [2] (c) Zhu <i>et al.</i> [11] (d) Li <i>et al.</i> [26] (e) Yang <i>et al.</i> [3] (f) Qu <i>et al.</i> [30] (g) kim <i>et al.</i> [31] (h) Dhara <i>et al.</i> [20] (i) Ju <i>et al.</i> [29] (J) Gautam <i>et al.</i> [C4], (k) Ours (l) GT (<i>Best viewed on zoom-in</i>).	62

5.5	Qualitative dehazing comparison with other progressive techniques on FRIDA dataset [28]. (a) Synthetic haze image. (b) He <i>et al.</i> [2] (c) Zhu <i>et al.</i> [11] (d) Li <i>et al.</i> [26] (e) Yang <i>et al.</i> [3] (f) Qu <i>et al.</i> [30] (g) kim <i>et al.</i> [31] (h) Dhara <i>et al.</i> [20] (i) Ju <i>et al.</i> [29] (J) Gautam <i>et al.</i> [C4], (k) Ours (l) GT (<i>Best viewed on zoom-in</i>).	63
5.6	Qualitative dehazing comparison with other progressive techniques on NTIRE-2020 dataset [32]. (a) Non-homogenous haze image. (b) He <i>et al.</i> [2] (c) Zhu <i>et al.</i> [11] (d) Li <i>et al.</i> [26] (e) Yang <i>et al.</i> [3] (f) Qu <i>et al.</i> [30] (g) kim <i>et al.</i> [31] (h) Dhara <i>et al.</i> [20] (i) Ju <i>et al.</i> [29] (J) Gautam <i>et al.</i> [C4], (k) Ours (l) GT (<i>Best viewed on zoom-in</i>).	63
5.7	Ablation study qualitative results on the synthetic RESIDE- β SOTS dataset [1]. (a) Haze image. (b) GT. (c) Case-1. (d) Case-2. (e) Case-3. (f) Case-4. (g) Case-5. (<i>Best viewed with zoom-in</i>).	64

ABBREVIATIONS

DCP	Dark Channel Prior
CLP	Color Line Prior
CEP	Color Ellipsoid Prior
HLP	Haze Line Prior
AIP	Atmospheric Illumination Prior
FADE	Fog Aware Density Evaluator
ATTF	Adaptive Trigonometric Transformation Function
RHEDCT	Regularized-Histogram-Equalization and Discrete-Cosine-Transform
CCP	Color Constancy Prior
MCP	Median Channel Prior
WMCP	Weighted Median Channel Prior
AOD-Net	All-in One Dehazing Network
FAMED-Net	Fast and Accurate Multi-Scale End-to-End Dehazing Network
DCPDN	Densely Connected Pyramid Dehazing Network
CNN	Convolutional Neural Network
DCNN	Deep Convolutional Neural Network
MSCNN	Multi-scale Convolutional Neural Network
DRL	Deep Residual Learning
GFN	Gated Fusion Network
GAN	Generative Adversarial Network
EPDN	Enhanced pix2pix Dehazing Network
DD-CycleGAN	Double-Discriminator Cycle-Consistent Adversarial Networks
GIF	Guided Image Filter
LSTM	Long Short Term Memory
HQS	Half-Quadratic Splitting

NOTATION

I	Hazy Image
J	Haze-free Image
B	Image luminosity
\mathbf{x}	Pixel Coordinates
A_∞	Global air-light
β	Scattering coefficient of the medium
d	Scene-depth
T	Transmission-map
\hat{T}	Estimated Transmission-map
\mathbb{R}	Set of Real numbers
Ω	Local-patch
\mathbb{N}	Total number of pixels in image
min	Minimum filter
max	Maximum filter
med	Median filter
φ	Small positive value for computational stability
c	color-channel
K_B	Brightest pixel set
K_b	Brighter pixel set
σ	Standard deviation of the input haze image
\ominus	Erosion operator
ζ	Square structuring element
E_m	Edge-modulation term
Υ	Edge-modulation index
δ	Exponent parameter
\mathcal{K}	Laplacian kernel
λ	Unsharp masking parameter
\mathcal{K}	Laplacian kernel
U	Identity matrix