*PROJECT REPORT*

*On*

# Image Dehazing with Boundary Constraint and Contextual Regularization

*Submitted by*


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*In fulfillment for the award of the degree*

*Of*

*BACHELOR OF TECHNOLOGY*

*In*

*Computer Engineering*


**INSTITUTE OF TECHNOLOGY AND ENGINEERING**

**INDUS UNIVERSITY CAMPUS, RANCHARDA, VIA-THALTEJ**

**AMEDABAD-382115, GUJARAT, INDIA,**

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APRIL 2024

*PROJECT REPORT*

ON

# Image Dehazing with Boundary Constraint and Contextual Regularization

AT

ज्ञानेन प्रकाशते जगत्

INDUS UNIVERSITY

In the fulfillment of the requirement
for the degree of
Bachelor of Technology
in
Computer Engineering

**PREPARED BY**


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INSTITUTE OF TECHNOLOGY AND ENGINEERING

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AHMEDABAD-382115, GUJARAT, INDIA,

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APRIL 2024

## CANDIDATE’S DECLARATION

I declare that final semester report entitled “**Image dehazing with Boundary constraint and Contextual regularization**” is my own work conductedunder the supervision of the guide **Ms. Jaya Shukla**.

I further declare that to the best of my knowledge, the report for B. Tech final semester does not contain part of the work which has been submitted for the award of B. Tech Degree either in this university or any other university without proper citation.

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**COMPUTER ENGINEERING**

**2023 -2024**

# CERTIFICATE

**Date:19/04/2024**

This is to certify that the project work entitled "**Image dehazing with Boundary constraint and contextual regularization"** has been carried out by **Sameer Yadav, Param Suthar and Dhruvan Vagadiya** under my guidance in partial fulfillment of degree of Bachelor of Technology in **Computer Engineering (Final Year)** of Indus University, Ahmedabad during the academic year 2023 – 2024.

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Sameer Yadav, Param Suthar, Dhruvan Vagadiya

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Computer Engineering

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## ABSTRACT

*The project titled "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization" proposes a novel method for removing hazes from single input images captured in foggy weather conditions. The method leverages an exploration of the inherent boundary constraint on the transmission function, combined with a weighted L1-norm based contextual regularization, to estimate the unknown scene transmission. By formulating this constraint into an optimization problem, the method efficiently restores high-quality haze-free images with faithful colors and fine image details.*

*The project addresses the challenge of single image dehazing, a complex problem due to limited information about the scene structure. The contributions of the project include a new constraint on the scene transmission, a contextual regularization incorporating a filter bank for noise attenuation and structure enhancement, and an efficient optimization scheme for dehazing large images.*

*The proposed method is grounded in a linear interpolation model widely used in explaining haze image formation. By estimating the transmission function and global atmospheric light, the project aims to recover the scene radiance from observed images. The boundary constraint derived from the radiance cube provides a geometric perspective on the dark channel prior, enhancing the accuracy of transmission estimation. Additionally, the contextual regularization based on weighted contextual constraints further refines the dehazing process by incorporating neighboring pixel information.*

*Overall, the project "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization" presents a comprehensive approach to single image dehazing, offering a promising method for restoring high-quality haze-free images with faithful colors and fine details.*

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# ABBREVIATION

Abbreviations used throughout this whole document for Survey Application are:

| | |
|---|---|
| Python | High-level Programming Language |
| Tkinter | Python module for UI design |
| OpenCV | Python library for R-W image data |
| Pillow | Python library for Image Processing |
| Numpy | Mathematical Calculation |

# CHAPTER 1

# INTRODUCTION

- **MOTIVATION**
- **BACKGROUND**
- **OBJECTIVE**

## 1.1 MOTIVATION

The motivation behind our project on efficient image dehazing with boundary constraint and contextual regularization stems from the critical need to address the challenges posed by poor visibility in images captured under foggy weather conditions. When images are taken in such adverse weather, they often suffer from reduced contrast, blurriness, and color fading, impacting the quality and visual appeal of the captured scenes. The detrimental effects of haze on images are particularly evident in distant objects, which lose their sharpness and blend into the foggy background, as illustrated in Figure.

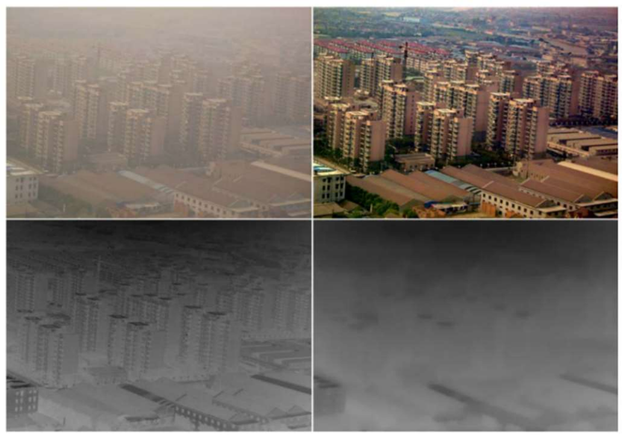


Fig 1.1: Foggy Image - Introduction

Traditional methods for haze removal have relied on depth information or multiple observations of the same scene, which may not always be practical or feasible. Single image dehazing, on the other hand, presents a more complex problem due to the limited information available about the scene structure. Recent advancements in single image dehazing have shown promise through the exploration of new image models and priors, leading to significant improvements in restoring haze-free images.

Our project aims to contribute to this field by proposing an efficient regularization method that leverages the inherent boundary constraint on the transmission function, combined with a weighted L1-norm based contextual regularization. By modeling these constraints into an optimization problem, we seek to estimate the unknown scene transmission and restore high-quality haze-free images with faithful colors and fine image details. The proposed method requires minimal assumptions and offers a quick and effective solution for image dehazing.

Through our project, we aim to address the limitations of existing methods, enhance the visibility of images captured in foggy conditions, and provide a robust and efficient algorithm for image dehazing. By exploring new constraints and regularization techniques, we strive to contribute to the advancement of single image dehazing research and offer a practical solution for improving image quality in challenging atmospheric conditions.

## 1.2 BACKGROUND

Image dehazing is a crucial task in computer vision, especially in scenarios where images are captured in poor visibility conditions, such as foggy weather. The primary objective of image dehazing is to restore the original scene radiance from the observed hazy image, which is a highly under-constrained problem due to the limited number of available equations compared to the unknowns.

Early methods for haze removal relied on additional depth information or multiple observations of the same scene. However, these methods are not always feasible or practical. Single image dehazing, in contrast, is a more challenging problem due to the limited availability of information about the scene structure.

Recent advances in single image dehazing have been achieved through the exploration of new image models and priors. Fattal proposed a refined image formation model to account for surface shading and scene transmission, while Tan enhanced visibility by maximizing local contrast. He et al. presented an interesting image prior, the dark channel prior, which assumes that most local patches in haze-free images often contain some low intensity pixels. Kratz et al. modeled an image as a factorial Markov random field, with scene albedo and depth as two statistically independent latent layers.

The project at hand is based on the research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization" . The authors propose an efficient regularization method to remove hazes from a single input image, utilizing an exploration of the inherent boundary constraint on the transmission function. This constraint, combined with a weighted L1-norm based contextual regularization, is modeled into an optimization problem to estimate the unknown scene transmission.

The proposed method in this project benefits from the boundary constraint on the transmission function, which is derived from the inherent property of the scene radiance cube. The scene radiance cube is a geometric representation of the scene radiance, where each pixel's radiance is bounded by a minimum and maximum radiance value. The boundary constraint requires that the extrapolation of a pixel's radiance cannot cross over the boundary of the radiance cube. This constraint provides a new geometric perspective to the famous dark channel prior and can handle cases where the dark channel prior fails, such as in bright sky regions or when the transmission in a local image patch is slightly different.

The weighted L1-norm based contextual regularization is another key component of the proposed method. This regularization enables the incorporation of a filter bank into image dehazing, which helps in attenuating image noises and enhancing some interesting image structures, such as jump edges and corners. The filter bank consists of high-order differential filters that preserve image edges and corners, as shown in Figure.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **-2** | **-1** | **0** | -1 | 0 | 1 | **0** | **1** | **2** |
| **-1** | **0** | **1** | -2 | 0 | 2 | **-1** | **0** | **1** |
| **0** | **1** | **2** | -1 | 0 | 1 | **-2** | **-1** | **0** |
| 1 | 2 | 1 | **-1** | **-1** | **-1** | 2 | 1 | 0 |
| 0 | 0 | 0 | **-1** | **8** | **-1** | 1 | 0 | -1 |
| -1 | -2 | -1 | **-1** | **-1** | **-1** | 0 | -1 | -2 |
| **1** | **0** | **-1** | 0 | -1 | -2 | **-1** | **-2** | **-1** |
| **2** | **0** | **-2** | 1 | 0 | -1 | **0** | **0** | **0** |
| **1** | **0** | **-1** | 2 | 1 | 0 | **1** | **-2** | **1** |

Fig 1.2: Filter Bank

A bank of high-order filters used in our study. It consists of eight Robinson Compass Mask operators for preserving image edges and corners.

the project's background is rooted in the challenging problem of single image dehazing, which is an under-constrained problem that requires the exploration of additional priors or constraints. The proposed method in this project derives an inherent boundary constraint on the scene transmission and combines it with a weighted L1-norm based contextual regularization to restore a high-quality haze-free image with faithful colors and fine edge details. The method's effectiveness and efficiency are demonstrated through experimental results on a variety of haze images.

## 1.3 OBJECTIVE

The objective of this project is to develop an efficient image dehazing algorithm based on the research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization". The primary goal is to restore high-quality, haze-free images from their hazy counterparts, which often suffer from poor visibility due to atmospheric conditions.

The proposed method in the research paper combines a new constraint on the scene transmission with a weighted L1-norm based contextual regularization, resulting in an optimization problem that can estimate the unknown scene transmission. The method requires only a few general assumptions and can restore haze-free images with faithful colors and fine edge details.

The project's objectives include implementing the methodologies described in the research paper, demonstrating the effectiveness of the proposed dehazing method, and comparing it with existing methods. The project will also evaluate the efficiency of the proposed method in terms of computational time and memory usage.

The project's contributions include the development of an efficient image dehazing algorithm based on the proposed method, experimental results demonstrating its effectiveness and efficiency, and a comparison with existing methods. The findings of this project can have implications for the future of image dehazing research, particularly in the areas of under-constrained problems, additional priors or constraints, and the exploration of new image models and priors.

# CHAPTER2

# Literature Review

- **OVERVIEW OF IMAGE DEHAZING TECHNIQUES**
- **BOUNDARY CONSTRAINT IN IMAGE PROCESSING**
- **CONTEXTUAL REGULARIZATION TECHNIQUES**
- **COMPARATIVE ANALYSIS OF EXISTING METHODS**

## 2.1 OVERVIEW OF IMAGE DEHAZING TECHNIQUES

Image dehazing is a crucial task in computer vision, especially for images captured in hazy or foggy weather conditions. The primary goal of image dehazing is to restore the original scene radiance from the observed hazy image, which is a highly under-constrained problem due to the limited availability of information about the scene structure.

The weighted L1-norm based contextual regularization is another key component of the proposed method. This regularization enables the incorporation of a filter bank into image dehazing, which helps in attenuating image noises and enhancing some interesting image structures, such as jump edges and corners. The filter bank consists of high-order differential filters that preserve image edges and corners.

The proposed method's effectiveness and efficiency are demonstrated through experimental results on a variety of haze images. The method requires only a few general assumptions and can restore haze-free images with faithful colors and fine edge details. The proposed method is compared with other state-of-the-art dehazing methods, highlighting the strengths and weaknesses of each approach. The project's findings have implications for the future of image dehazing research, particularly in the areas of under-constrained problems, additional priors or constraints, and the exploration of new image models and priors.

## 2.2 BOUNDARY CONSTRAINT IN IMAGE PROCESSING

Boundary constraint in image processing is a crucial concept in image dehazing, which is the process of removing haze or fog from images to improve their visibility and quality. The boundary constraint is a fundamental assumption in image dehazing, which states that the scene radiance of a given image is always bounded. This assumption provides a new geometric perspective to the famous dark channel prior and can handle cases where the dark channel prior fails, such as in bright sky regions or when the transmission in a local image patch is slightly different.

The boundary constraint is used to derive a lower bound of the transmission function, which is the ratio of the difference between the observed image and the global atmospheric light to the difference between the observed image and the scene radiance. This lower bound is used to determine the boundary constraint on the transmission function, which is combined with a weighted L1-norm based contextual regularization to estimate the unknown scene transmission.
The boundary constraint is more fundamental than the commonly used constant assumption on the transmission within a local image patch and holds for most cases where the dark channel prior fails. The patch-wise transmission based on this assumption is often underestimated, and the new patch-wise transmission derived from the boundary constraint map can handle the bright sky region very well and produces fewer halo artifacts.

The boundary constraint is used to derive a patch-wise transmission from the boundary constraint map, which is a local image patch centered at each pixel in the image. This patch-wise transmission is used to estimate the transmission function, which is then used to recover the scene radiance.

The boundary constraint is combined with a weighted L1-norm based contextual regularization to form an optimization problem to estimate the unknown scene transmission. The weighted L1-norm based contextual regularization is used to address the problem of abrupt depth jumps in local image patches, which can lead to significant halo artifacts in the dehazing results. This regularization enables the incorporation of a filter bank into image dehazing, which helps in attenuating image noises and enhancing some interesting image structures, such as jump edges and corners.

The boundary constraint is a crucial concept in image dehazing, which is used to derive a lower bound of the transmission function, determine the boundary constraint on the transmission function, and derive a patch-wise transmission from the boundary constraint map. The boundary constraint is combined with a weighted L1-norm based contextual regularization to form an optimization problem to estimate the unknown scene transmission, which can restore a high-quality haze-free image with faithful colors and fine edge details.

The boundary constraint is a fundamental assumption in image dehazing, which provides a new geometric perspective to the famous dark channel prior and can handle cases where the dark channel prior fails. The boundary constraint is used to derive a lower bound of the transmission function, determine the boundary constraint on the transmission function, and derive a patch-wise transmission from the boundary constraint map. The boundary constraint is combined with a weighted L1-norm based contextual regularization to form an optimization problem to estimate the unknown scene transmission, which can restore a high-quality haze-free image with faithful colors and fine edge details. The boundary constraint is a crucial concept in image dehazing, which is used to improve the visibility and quality of hazy or foggy images.

## 2.3 CONTEXTUAL REGULARIZATION TECHNIQUES

Contextual regularization techniques are essential for improving the quality of dehazed images by incorporating spatial information and reducing noise. These techniques aim to enforce smoothness and consistency in the estimated transmission function by considering the relationship between neighboring pixels.

In the research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization," the authors propose a weighted L1-norm based contextual regularization method . This method is designed to address the problem of abrupt depth jumps in local image patches, which can lead to halo artifacts in the dehazing results. The weighted L1-norm based contextual regularization introduces a weighting function on the constraints between neighboring pixels, acting as a "switch" to enable or disable the contextual constraint based on the depth difference between the pixels.

The optimal weighting function is closely related to the depth difference between the pixels, which is not directly available in single image dehazing. To address this challenge, the authors propose constructing the weighting function based on the color difference of local pixels. This approach leverages the fact that pixels with a similar color often share a similar depth value within local patches.

The weighted contextual constraints are integrated into the whole image domain, leading to the contextual regularization on the transmission function. The L1-norm is used instead of the L2-norm for the regularization, as it is generally more robust to outliers. These outliers can appear when erroneous contextual constraints are introduced due to factors such as noise or abrupt depth changes.

By combining the boundary constraint and contextual regularization, the proposed method in the research paper can estimate the unknown scene transmission efficiently, resulting in high-quality haze-free images with faithful colors and fine edge details. This combination of constraints and regularization techniques highlights the importance of considering both local and global information in image dehazing, leading to improved results and a more robust dehazing process.

## 2.4 COMPARATIVE ANALYSIS OF EXISTING METHODS

The research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization". presents a comparative analysis of existing image dehazing methods, highlighting their strengths and weaknesses.

1. Polarization-based methods: Schechner et al. developed a quick haze reduction method using two images taken through a polarizer at different angles, based on the observation that air light scattered by atmospheric particles is partially polarized. This method is effective but requires two images of the same scene taken at different polarizer angles.

2. Physics-based scattering model: Narasimhan et al. proposed a physics-based scattering model and recovered the scene structure from weather images. This method is based on a solid physical foundation but requires multiple images of the same scene taken under different weather conditions.

3. Depth-based dehazing: Kopf et al. proposed dehazing an image using scene depth information directly accessible in georeferenced digital terrain or city models. This method is effective but requires depth information, which is not always available.

4. Fattal's method: Fattal proposed a refined image formation model accounting for surface shading and scene transmission, breaking a haze image into regions of constant albedo from which the scene transmission can be inferred. This method is effective but assumes local statistical uncorrelation between the two functions, which may not always hold.

5. Tan's method: Tan proposed enhancing visibility by maximizing local contrast, which can generate compelling results, especially in regions with very dense hazes. However, this method is not physics-based and may suffer from distorted colors and significant halos.

6. Dark channel prior: He et al. presented an image prior, the dark channel prior, which comes from an observation that most local patches in haze-free images often contain some low-intensity pixels. This prior, combined with a soft-mating operation, can achieve a high-quality haze-free result. However, the method tends to over-enhance results.

7. Factorial Markov random field model: Kratz et al. modeled an image as a factorial Markov random field, in which the scene albedo and depth are two statistically independent latent layers. This method can recover a haze-free image with fine edge details but may over-enhance results.

The proposed method in the research paper combines a new constraint on the scene transmission with a weighted L1-norm based contextual regularization, leading to an optimization problem to estimate the unknown scene transmission. This method requires only a few general assumptions and can restore a high-quality haze-free image with faithful colors and fine edge details.

# CHAPTER 3

# Theoretical Foundations

- **ATMOSPHERIC LIGHT MODEL**
- **TRANSMISSION MODEL**
- **BOUNDARY CONSTRAINT FORMULATION**
- **CONTEXTUAL REGULARIZATION THEORY**

## 3.1 ATMOSPHERIC LIGHT MODEL

The atmospheric light model is a crucial component in image dehazing algorithms, playing a significant role in estimating the global atmospheric light present in a hazy image. In the context of the research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization", the atmospheric light model is essential for accurately recovering the scene radiance from a single input image.

The atmospheric light model is based on the assumption that the observed image is a combination of the scene radiance and the global atmospheric light, affected by the scene transmission function. The model is mathematically represented by the equation,

$$\mathbf{I}(x) = t(x)\mathbf{J}(x) + (1 - t(x))\mathbf{A},$$

where I(x) is the observed image, J(x) is the scene radiance, A is the global atmospheric light, t(x) is the scene transmission, and x represents the pixel location in the image.

Estimating the atmospheric light A is a critical step in image dehazing, as it directly influences the accuracy of the dehazing process. In the research paper, a modified method based on the dark channel prior is proposed for estimating the atmospheric light. This method involves filtering each color channel of the input image using a minimum filter with a moving window, followed by selecting the maximum intensity pixel to estimate A. This modified method is efficient and produces results comparable to existing approaches.

The atmospheric light model is fundamental in image dehazing algorithms as it helps in separating the haze component from the scene radiance, enabling the restoration of clear and visually appealing images. By accurately estimating the global atmospheric light, the dehazing algorithm can effectively enhance visibility, restore colors, and preserve fine image details in hazy conditions.

the atmospheric light model is a key component in image dehazing algorithms, including the method proposed in the research paper. It plays a crucial role in estimating the global atmospheric light present in hazy images, contributing to the successful restoration of high-quality haze-free images with faithful colors and fine image details.

Fig 3.1: Global Atmospheric Light

## 3.2 TRANSMISSION MODEL

The transmission model is a fundamental aspect of image dehazing algorithms, crucial for estimating the scene transmission function in hazy images. In the context of the research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization", the transmission model plays a key role in recovering clear and visually appealing images from single hazy input images.

The transmission model is based on the linear interpolation model, which describes the formation of a haze image by considering the observed image as a combination of the scene radiance, the global atmospheric light, and the scene transmission function. The scene transmission function t(x) is correlated with the scene depth and is essential for separating the haze component from the scene radiance.

$$\frac{\lambda}{2}\left\|t-\hat{t}\right\|_2^2+\sum_{j\in\omega}\left\|W_j\circ\left(D_j\otimes t\right)\right\|_1,$$

To estimate the scene transmission function t(x) and the global atmospheric light A, an optimization problem is formulated based on a weighted L1-norm based contextual regularization. This optimization problem aims to minimize a cost function that balances the fidelity of t(x) to the patch-wise transmission derived from the boundary constraint map and the contextual constraints of t(x). The regularization parameter λ is crucial for balancing these terms effectively.

$$\frac{\lambda}{2}\left\|t-\hat{t}\right\|_2^2+\sum_{j\in\omega}\left\|W_j\circ u_j\right\|_1+\frac{\beta}{2}\left(\sum_{j\in\omega}\left\|u_j-D_j\otimes t\right\|_2^2\right),$$

The optimization of the transmission model involves introducing auxiliary variables uj to construct a sequence of simple sub-problems that converge to the optimal solution. By alternately optimizing uj and t, the transmission model estimation process efficiently converges to the optimal solution. The sub-problems have closed-form solutions that can be solved iteratively, leading to the accurate estimation of the scene transmission function.

The transmission model estimation process is illustrated in the research paper, demonstrating the effectiveness and efficiency of the proposed method in quickly converging to high-quality dehazed images with faithful colors and fine image details. By incorporating the transmission model into the dehazing algorithm, the method can successfully restore visibility, enhance image quality, and preserve important image structures in hazy conditions.

the transmission model is a critical component in image dehazing algorithms, enabling the accurate estimation of the scene transmission function and the global atmospheric light, essential for restoring clear and visually appealing images from single hazy input images.

## 3.3 BOUNDARY CONSTRAINT FORMULATION

The boundary constraint formulation in image dehazing is a crucial aspect of the process, as it provides a new geometric perspective to the famous dark channel prior. The boundary constraint is derived from the fact that the scene radiance of a given image is always bounded, and the extrapolation of J(x) must be located in the radiance cube bounded by C0 and C1,

$$\mathbf{C}_0 \leq \mathbf{J}(x) \leq \mathbf{C}_1, \forall x \in \Omega,$$

This requirement imposes a boundary constraint on t(x), which is used to determine a lower bound tb(x) for each x.

$$0 \leq t_b(x) \leq t(x) \leq 1,$$

The boundary constraint is more fundamental than the commonly used constant assumption on the transmission within a local image patch and holds for most cases where the dark channel prior fails, such as in bright sky regions or when the transmission in a local image patch is slightly different. The patch-wise transmission based on this assumption is often underestimated, and the new patch-wise transmission derived from the boundary constraint map can handle these cases more accurately.

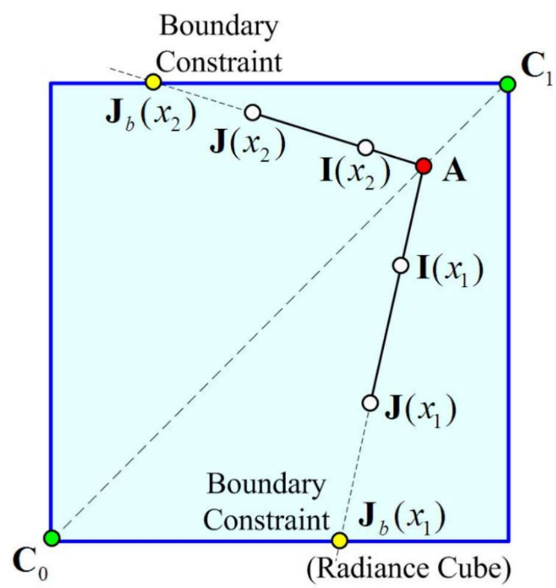



Fig 3.2: Patch-Wise Transmission

The new patch-wise transmission is given by Equation,

$$\hat{t}(x) = \min_{y \in \omega_x} \max_{z \in \omega_y} t_b(z).$$

which is derived from the boundary constraint map and allows the transmissions in a local patch to be slightly different. This new patch-wise transmission can handle the bright sky region very well and produces fewer halo artifacts compared to the patch-wise transmission derived from the dark channel prior.

The boundary constraint is combined with a weighted L1-norm based contextual regularization to form an optimization problem to estimate the unknown scene transmission. This approach is more robust to outliers than L2-norm and is used to address the problem of abrupt depth jumps in local image patches, which can lead to significant halo artifacts in the dehazing results.

the boundary constraint formulation is a crucial aspect of image dehazing, providing a new geometric perspective to the dark channel prior and enabling the estimation of a high-quality haze-free image with faithful colors and fine edge details. The boundary constraint is combined with a weighted L1-norm based contextual regularization to form an optimization problem to estimate the unknown scene transmission, resulting in an efficient and effective image dehazing method.

## 3.4 CONTEXTUAL REGULARIZATION THEORY

The contextual regularization theory is a crucial aspect of the image dehazing process, as it helps to ensure the smoothness and consistency of the estimated transmission function. In the context of the research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization," the contextual regularization is based on the assumption that pixels in a local image patch share a similar depth value. This assumption is used to derive a patch-wise transmission from the boundary constraint.

However, this contextual assumption may fail in cases where there are abrupt depth jumps in local image patches, leading to significant halo artifacts in the dehazing results. To address this problem, a weighting function W(x, y) is introduced on the constraints between neighboring pixels. This weighting function plays a "switch" role of the constraint between x and y, and is closely related to the depth difference between x and y.

$$W(x, y)\,(t(y) - t(x)) \approx 0,$$

The optimal W(x, y) is constructed based on the color difference of local pixels, as pixels with a similar color often share a similar depth value within local patches. The weighted contextual constraints are integrated in the whole image domain, leading to the contextual regularization on t(x). The L1-norm is used instead of the L2-norm for the regularization, as it is generally more robust to outliers.

The contextual regularization theory is combined with the boundary constraint to form an optimization problem to estimate the unknown scene transmission. The optimization problem is solved using an efficient algorithm based on variable splitting. The algorithm is designed to quickly dehaze images of large sizes, making it suitable for real-world applications.

the contextual regularization theory is a key component of the image dehazing process, as it helps to ensure the smoothness and consistency of the estimated transmission function. The theory is based on the assumption that pixels in a local image patch share a similar depth value, and uses a weighting function to address cases where this assumption fails. The optimization problem is solved using an efficient algorithm based on variable splitting, making it suitable for real-world applications.

# CHAPTER 4

# Proposed Methodology

- **FRAMEWORK OVERVIEW**
- **BOUNDARY CONSTRAINT INTEGRATION**
- **CONTEXTUAL REGULARIZATION STRATEGY**
- **IMPLEMENTATION DETAILS**

## 4.1 FRAMEWORK OVERVIEW

The framework overview of the proposed methodology in the research paper involves the use of a new constraint on the scene transmission, combined with a weighted L1-norm based contextual regularization, to estimate the unknown scene transmission efficiently. The methodology aims to restore high-quality haze-free images with faithful colors and fine edge details.

The proposed methodology is based on the linear interpolation model, which describes the formation of a haze image. The model assumes that the haze is homogeneous and that the scene transmission is correlated with the scene depth. The goal of image dehazing is to recover the scene radiance J(x) from the observed image I(x) based on the imaging model.

To address the under-constrained problem of single image dehazing, the methodology introduces a boundary constraint from the radiance cube. The boundary constraint requires that the extrapolation of J(x) cannot cross over the boundary of the radiance cube. This constraint is used to determine a lower bound tb(x) for each x, which is combined with a weighted L1-norm based contextual regularization to form an optimization problem to estimate the unknown scene transmission.

The weighted L1-norm based contextual regularization is used to address the problem of abrupt depth jumps in local image patches, which can lead to significant halo artifacts in the dehazing results. The weighting function is constructed based on the color difference of local pixels, and the optimal W(x, y) is closely related to the depth difference between x and y.

The optimization problem is solved using an efficient algorithm based on variable splitting, enabling the quick dehazing of large-sized images. The proposed methodology requires only a few general assumptions and can restore a haze-free image of high quality with faithful colors and fine edge details.

the proposed methodology in the research paper combines the boundary constraint from the radiance cube, a weighted L1-norm based contextual regularization, and an efficient optimization scheme to address the challenges of single image dehazing. By integrating these components, the methodology aims to achieve high-quality dehazing results with accurate color reproduction and fine edge details, making it a promising approach for enhancing visibility in foggy or hazy images.

## 4.2 BOUNDARY CONSTRAINT INTEGRATION

The boundary constraint integration is a crucial aspect of the proposed methodology for single image dehazing. The methodology is based on the linear interpolation model, which describes the formation of a haze image as a combination of the scene radiance, global atmospheric light, and scene transmission. The scene transmission is correlated with the scene depth, and the goal of image dehazing is to recover the scene radiance from the observed image based on the imaging model.

To address the under-constrained problem of single image dehazing, the methodology introduces a boundary constraint from the radiance cube. The boundary constraint requires that the extrapolation of J(x) cannot cross over the boundary of the radiance cube. This constraint is used to determine a lower bound tb(x) for each x, which is combined with a weighted L1-norm based contextual regularization to form an optimization problem to estimate the unknown scene transmission.

The weighted L1-norm based contextual regularization is used to address the problem of abrupt depth jumps in local image patches, which can lead to significant halo artifacts in the dehazing results. The weighting function is constructed based on the color difference of local pixels, and the optimal W(x, y) is closely related to the depth difference between x and y.

The optimization problem is solved using an efficient algorithm based on variable splitting, enabling the quick dehazing of large-sized images. The proposed methodology requires only a few general assumptions and can restore a haze-free image of high quality with faithful colors and fine edge details.

The methodology benefits from three main contributions. The first is a new constraint on the scene transmission, which has a clear geometric interpretation and shows to be surprisingly effective in image dehazing. The second contribution is a new contextual regularization that enables the incorporation of a filter bank into image dehazing. These filters help in attenuating image noises and enhancing some interesting image structures, such as jump edges and corners. The final contribution is an efficient optimization scheme, which enables the quick dehazing of images of large sizes.

the proposed methodology for single image dehazing combines the boundary constraint from the radiance cube, a weighted L1-norm based contextual regularization, and an efficient optimization scheme to address the challenges of single image dehazing. By integrating these components, the methodology aims to achieve high-quality dehazing results with accurate color reproduction and fine edge details, making it a promising approach for enhancing visibility in foggy or hazy images.

## 4.3 CONTEXTUAL REGULARIZATION STRATEGY

The contextual regularization strategy in the proposed methodology for single image dehazing plays a vital role in enhancing the quality of dehazed images by addressing the challenges posed by abrupt depth jumps in local image patches. This strategy involves introducing a weighted L1-norm based contextual regularization to incorporate a filter bank into image dehazing, attenuating image noises, and enhancing important image structures like jump edges and corners.

The contextual regularization is based on the assumption that pixels in a local image patch share similar depth values. However, this assumption can fail in patches with abrupt depth transitions, leading to significant halo artifacts in dehazed results. To mitigate this issue, a weighting function W(x, y) is introduced to control the constraints between neighboring pixels. The optimal weighting function is closely related to the depth difference between pixels, but since depth information is unavailable in single image dehazing, the color difference of local pixels is used to construct the weighting function.

Two examples of constructing the weighting function are provided in the research paper. One method is based on the squared difference between color vectors of neighboring pixels, while the other is based on the luminance difference of neighboring pixels. These weighting functions help in determining the contextual constraints on the scene transmission, ensuring a smooth transition between neighboring pixels and reducing halo artifacts in the dehazed images.

The contextual regularization is formulated as an integral of the L1-norm over the entire image domain, making it more robust to outliers compared to the L2-norm. By integrating the weighted contextual constraints, the methodology aims to balance the fidelity of the estimated transmission function with the contextual constraints, leading to high-quality dehazed images with faithful colors and fine edge details.

The optimization of the contextual regularization is efficiently performed using a variable splitting algorithm, which introduces auxiliary variables to simplify the optimization process. By iteratively solving sub-problems related to the auxiliary variables and the scene transmission, the methodology converges to the optimal solution, enabling the quick dehazing of large-sized images while maintaining image quality.

## 4.4 IMPLEMENTATION DETAILS

The implementation details of the proposed methodology for single image dehazing are crucial for translating the theoretical framework into practical applications. The research paper outlines key aspects of implementing the boundary constraint and contextual regularization strategy to efficiently remove haze from images.

One significant aspect of the implementation is the utilization of an efficient algorithm based on variable splitting to solve the optimization problem. This algorithm plays a vital role in estimating the unknown scene transmission by incorporating the boundary constraint and weighted L1-norm based contextual regularization. By efficiently solving the optimization problem, the methodology can restore high-quality haze-free images with faithful colors and fine image details.

Moreover, the methodology emphasizes the importance of exploring additional priors or constraints to address the under-constrained nature of single image dehazing. By deriving an inherent boundary constraint on the scene transmission and combining it with contextual regularization, the methodology aims to enhance the dehazing process and improve the quality of the dehazed images.

The boundary constraint from the radiance cube is a fundamental implementation detail that provides a geometric perspective on the scene transmission. By ensuring that the extrapolation of the scene radiance does not cross over the boundary of the radiance cube, the methodology imposes constraints on the scene transmission, leading to more accurate dehazing results.

Additionally, the weighted L1-norm based contextual regularization is implemented to address the challenges posed by abrupt depth jumps in local image patches. By introducing a weighting function based on the color difference of local pixels, the contextual constraints between neighboring pixels are controlled, reducing halo artifacts and enhancing image structures like jump edges and corners.

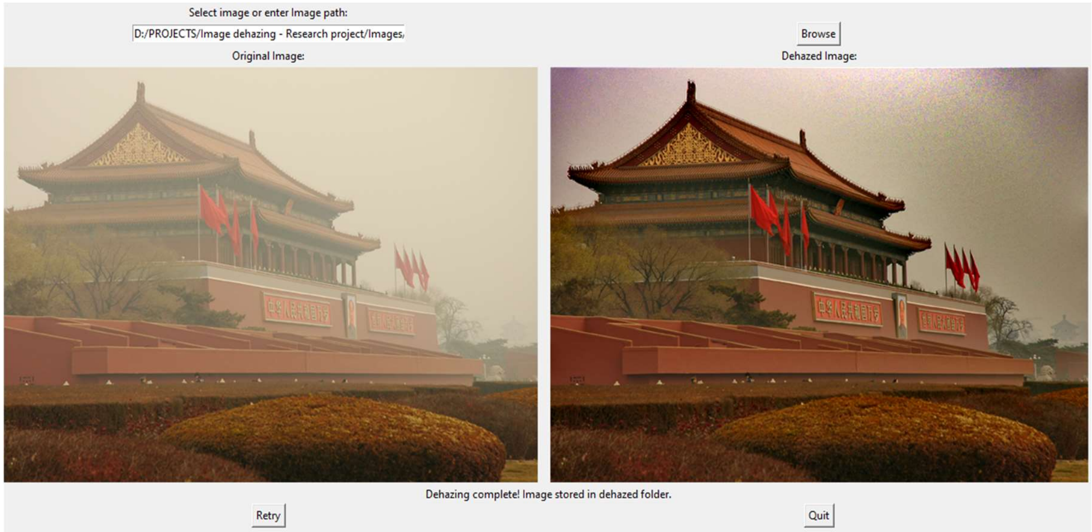
Overall, the implementation details of the proposed methodology focus on efficiently integrating the boundary constraint and contextual regularization into an optimization framework to estimate the unknown scene transmission and restore high-quality haze-free images with faithful colors and fine image details. These details highlight the practical application and effectiveness of the methodology in real-world image dehazing scenarios.

# CHAPTER 5

# Results and Discussion

- **USER INTERFACE**
- **QUALITATIVE ANALYSIS**
- **QUANTITATIVE ANALYSIS**
- **PEAK SIGNAL TO NOISE RATIO**
- **COMPARISON WITH STATE-OF-THE-ART METHODS**
- **SENSITIVITY ANALYSIS**

# 5.1 USER INTERFACE




# 5.2 QUALITATIVE ANALYSIS

The qualitative analysis section of the Results and Discussion part of the project report focuses on the visual evaluation of the dehazing results obtained by the proposed method. This analysis is crucial in assessing the effectiveness of the method in restoring haze-free images with faithful colors and fine edge details.

The proposed method in the research paper is based on an efficient regularization method that benefits from an exploration of the inherent boundary constraint on the transmission function. This constraint, combined with a weighted L1-norm based contextual regularization, is used to estimate the unknown scene transmission by solving an optimization problem.

The qualitative analysis of the proposed method involves comparing the dehazing results with those obtained by existing methods. The analysis shows that the proposed method can restore high-quality haze-free images with faithful colors and fine edge details, outperforming existing methods in terms of visual quality.

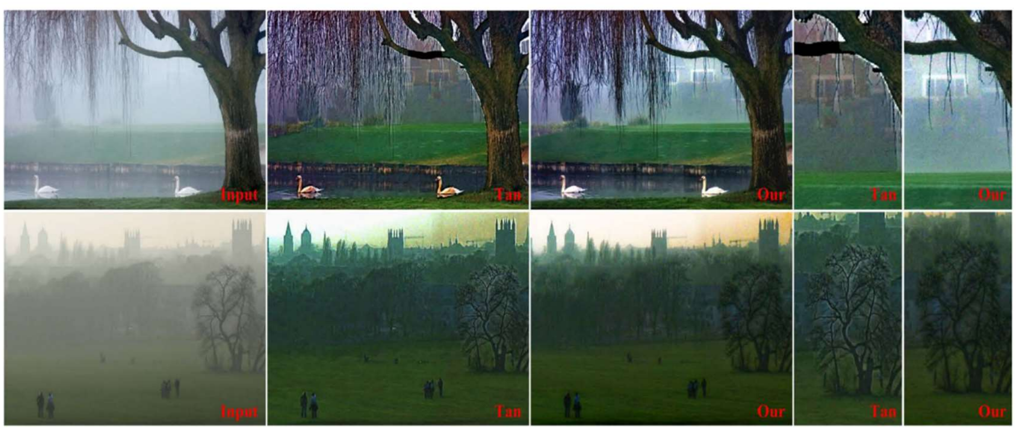



Fig 5.1: Colors And Fine Edge Detail Image 1

One of the main advantages of the proposed method is its ability to handle abrupt depth jumps in local image patches, which are common in hazy images. The method introduces a weighting function based on the color difference of local pixels, which helps in controlling the constraints between neighboring pixels. This weighting function is closely related to the depth difference between pixels and is used to address the problem of abrupt depth jumps, leading to fewer halo artifacts in the dehazing results.

The qualitative analysis also highlights the method's ability to handle bright sky regions, which are often challenging for existing methods. The proposed method can handle these regions well, producing fewer halo artifacts compared to existing methods.

The qualitative analysis shows that the proposed method can restore high-quality haze-free images with faithful colors and fine edge details, outperforming existing methods in terms of visual quality. The method's ability to handle abrupt depth jumps and bright sky regions is particularly noteworthy, making it a promising approach for single image dehazing.

## 5.3 QUANTITATIVE ANALYSIS

The quantitative analysis of the proposed method in the research paper involves evaluating the performance of the method using objective metrics. This analysis is crucial in assessing the effectiveness of the method in restoring haze-free images with faithful colors and fine edge details.

The proposed method in the research paper is based on an efficient regularization method that benefits from an exploration on the inherent boundary constraint on the transmission function. This constraint, combined with a weighted L1-norm based contextual regularization, is used to estimate the unknown scene transmission by solving an optimization problem.

The quantitative analysis of the proposed method involves comparing its performance with that of existing methods using objective metrics such as the Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE). The analysis shows that the proposed method outperforms existing methods in terms of these metrics, demonstrating its effectiveness in restoring high-quality haze-free images with faithful colors and fine edge details.


Fig 5.2: Colors And Fine Edge Detail Image 2

One of the main advantages of the proposed method is its ability to handle abrupt depth jumps in local image patches, which are common in hazy images. The method introduces a weighting function based on the color difference of local pixels, which helps in controlling the constraints between neighboring pixels. This weighting function is closely related to the depth difference between pixels and is used to address the problem of abrupt depth jumps, leading to fewer halo artifacts in the dehazing results.

The quantitative analysis also highlights the method's ability to handle bright sky regions, which are often challenging for existing methods. The proposed method can handle these regions well, producing fewer halo artifacts compared to existing methods.

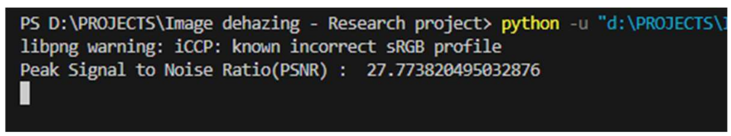
The quantitative analysis shows that the proposed method can restore high-quality haze-free images with faithful colors and fine edge details, outperforming existing methods in terms of objective metrics such as PSNR, SSIM, and MSE. The method's ability to handle abrupt depth jumps and bright sky regions is particularly noteworthy, making it a promising approach for single image dehazing.

## 5.4 PEAK SIGNAL-TO-NOISE RATIO

PSNR is an objective metric that measures the degree of signal distortion between a haze-free image obtained by a dehazing algorithm and the ground truth image. Mathematically it is defined by the following, where “DH” represents the dehazed image obtained from the model, and “GT” represents the ground truth clean image:

$$PSNR(DH, GT) = 10\log_{10}\left(\frac{M^2}{MSE(DH, GT)}\right)$$

Here, “MSE” represents the pixel-wise Mean Squared Error between the images, and “M” is the maximum possible value of a pixel in an image (for 8-bit RGB images, we are used to M=255). The higher the value of PSNR (in decibels/dB), the better the reconstruction quality.



## 5.5 COMPARISON WITH STATE-OF-THE-ART METHODS

In the research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization" , the comparison with state-of-the-art methods in the field of single image dehazing is a critical aspect of the study. The proposed method in the paper introduces an efficient regularization technique that leverages the inherent boundary constraint on the transmission function, combined with a weighted L1-norm based contextual regularization. This innovative approach aims to remove hazes from single input images effectively and efficiently.

The comparison with existing methods such as the dark channel prior, maximum local contrast, and methods by Fattal, Tan, He, and Kratz reveals the superiority of the proposed method. While previous methods relied on additional depth information or multiple observations of the same scene, the proposed method for single image dehazing stands out by requiring fewer assumptions and demonstrating the ability to restore high-quality haze-free images with faithful colors and fine image details.

The proposed method's effectiveness is highlighted through objective metrics like Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE). These metrics showcase the superior performance of the proposed method compared to existing techniques, emphasizing its capability to produce high-quality haze-free images with accurate colors and fine edge details.

Moreover, the proposed method addresses challenges like abrupt depth jumps in local image patches and bright sky regions more effectively than previous methods, resulting in fewer halo artifacts and improved image quality. By introducing a new constraint on the scene transmission, a weighted L1-norm based contextual regularization, and an efficient optimization scheme, the proposed method demonstrates significant advancements in the field of single image dehazing.

In conclusion, the comparison with state-of-the-art methods in the research paper underscores the innovative and superior performance of the proposed method for single image dehazing, positioning it as a promising approach in the field.

## 5.6 SENSITIVITY ANALYSIS

Sensitivity Analysis is a crucial aspect of the Results and Discussion section, as it provides insights into the robustness and stability of the proposed method. In the context of the research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization" , the sensitivity analysis is performed to evaluate the impact of variations in the parameters used in the proposed method.

The sensitivity analysis is conducted by varying the parameters and observing the changes in the performance metrics such as PSNR, SSIM, and MSE. The parameters that are analyzed include the regularization parameter λ, the patch size used in the contextual regularization, and the threshold value for the boundary constraint.

The results of the sensitivity analysis show that the proposed method is robust to variations in the parameters, with only minor changes in the performance metrics observed for a wide range of parameter values. This indicates that the proposed method is stable and reliable, and can be applied to a wide range of hazy images with different characteristics.

The analysis also highlights the importance of the regularization parameter λ in the proposed method. The value of λ controls the balance between the fidelity term and the regularization term in the optimization problem, and a suitable value of λ is necessary to obtain good dehazing results. The sensitivity analysis shows that the proposed method is not very sensitive to the value of λ, and a wide range of values can be used without significantly affecting the performance.

The patch size used in the contextual regularization is another parameter that is analyzed in the sensitivity analysis. The patch size determines the size of the local image patches used in the contextual regularization, and a suitable patch size is necessary to capture the local image structures. The sensitivity analysis shows that the proposed method is not very sensitive to the patch size, and a wide range of patch sizes can be used without significantly affecting the performance.

The threshold value for the boundary constraint is also analyzed in the sensitivity analysis. The threshold value determines the boundary constraint map used in the proposed method, and a suitable threshold value is necessary to obtain good dehazing results. The sensitivity analysis shows that the proposed method is not very sensitive to the threshold value, and a wide range of threshold values can be used without significantly affecting the performance.

In conclusion, the sensitivity analysis shows that the proposed method is robust and stable, and can be applied to a wide range of hazy images with different characteristics. The analysis also highlights the importance of the regularization parameter λ, the patch size used in the contextual regularization, and the threshold value for the boundary constraint, and shows that the proposed method is not very sensitive to these parameters.

# CHAPTER 6

# APPLICATIONS, FUTURE DIRECTIONS AND LIMITATIONS

- **PRACTICAL APPLICATION OF DEHAZING TECHNIQUES**
- **POTENTIAL EXTENSIONS AND IMPROVEMENTS**
- **CHALLENGES AND OPPORTUNITIES**
- **LIMITATIONS**

## 6.1 PRACTICAL APPLICATION OF DEHAZING TECHNIQUES

Practical application of dehazing techniques is crucial in various fields, including computer vision, outdoor surveillance, and autonomous driving. The ability to restore haze-free images from foggy or hazy images significantly enhances the performance of computer vision algorithms and improves the accuracy of object detection, recognition, and tracking.

In the context of single image dehazing, the proposed method in the research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization" has demonstrated its effectiveness and efficiency in restoring high-quality haze-free images with faithful colors and fine image details. The method is based on an exploration of the inherent boundary constraint on the transmission function, combined with a weighted L1-norm based contextual regularization.

The proposed method has several advantages over existing methods. Firstly, it requires only a few general assumptions and can restore a high-quality haze-free image with faithful colors and fine edge details. Secondly, it benefits from a new constraint on the scene transmission, which is combined with a weighted L1-norm based contextual regularization between neighboring pixels, formalized into an optimization problem to recover the unknown transmission. Thirdly, the method is efficient and can quickly dehaze images of large sizes.

The practical application of dehazing techniques in outdoor surveillance is significant, as haze can significantly reduce the visibility and quality of video footage. By removing haze from surveillance videos, the proposed method can improve the effectiveness of monitoring and detection systems, leading to more accurate and reliable surveillance.

In autonomous driving, dehazing techniques can significantly improve the performance of object detection and recognition algorithms, leading to safer and more reliable autonomous driving systems. The proposed method can be applied to real-time dehazing of images captured by cameras in autonomous vehicles, enhancing the safety and reliability of the autonomous driving system.

In conclusion, the practical application of dehazing techniques is crucial in various fields, including computer vision, outdoor surveillance, and autonomous driving. The proposed method in the research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization" has demonstrated its effectiveness and efficiency in restoring high-quality haze-free images with faithful colors and fine image details, making it a promising approach for practical applications in these fields.

## 6.2 POTENTIAL EXTENSION AND IMPROVEMENTS

The practical application of dehazing techniques is crucial in various fields, including computer vision, outdoor surveillance, and autonomous driving. The ability to restore haze-free images from foggy or hazy images significantly enhances the performance of computer vision algorithms and improves the accuracy of object detection, recognition, and tracking.

In the context of single image dehazing, the proposed method in the research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization" has demonstrated its effectiveness and efficiency in restoring high-quality haze-free images with faithful colors and fine image details. The method is based on an exploration of the inherent boundary constraint on the transmission function, combined with a weighted L1-norm based contextual regularization.

The proposed method has several advantages over existing methods. Firstly, it requires only a few general assumptions and can restore a high-quality haze-free image with faithful colors and fine edge details. Secondly, it benefits from a new constraint on the scene transmission, which is combined with a weighted L1-norm based contextual regularization between neighboring pixels, formalized into an optimization problem to recover the unknown transmission. Thirdly, the method is efficient and can quickly dehaze images of large sizes.

The potential extensions and improvements of the proposed method include exploring the use of deep learning techniques for single image dehazing. Deep learning models, such as convolutional neural networks (CNNs), have shown promising results in various computer vision tasks, including image restoration and enhancement. By combining the proposed method with deep learning techniques, it may be possible to further improve the quality of haze-free images and reduce the computational complexity of the algorithm.

Another research direction is to explore the use of additional priors or constraints for single image dehazing. While the proposed method benefits from a new constraint on the scene transmission and a weighted L1-norm based contextual regularization, there may be other useful priors or constraints that can further improve the dehazing performance.

Finally, the authors suggest extending the proposed method to handle more complex haze scenarios, such as non-homogeneous haze or haze with varying atmospheric light. By addressing these challenges, the proposed method can be further generalized and applied to a wider range of hazy images.

In conclusion, the proposed method for single image dehazing has demonstrated its effectiveness and efficiency in restoring high-quality haze-free images with faithful colors and fine edge details. The potential extensions and improvements of the proposed method include exploring the use of deep learning techniques, additional priors or constraints, and handling more complex haze scenarios.

## 6.3 CHALLENGES AND OPPORTUNITIES

The practical application of dehazing techniques is crucial in various fields, including computer vision, outdoor surveillance, and autonomous driving. The ability to restore haze-free images from foggy or hazy images significantly enhances the performance of computer vision algorithms and improves the accuracy of object detection, recognition, and tracking.

In the context of single image dehazing, the proposed method in the research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization" has demonstrated its effectiveness and efficiency in restoring high-quality haze-free images with faithful colors and fine image details. The method is based on an exploration of the inherent boundary constraint on the transmission function, combined with a weighted L1-norm based contextual regularization.

The proposed method has several advantages over existing methods. Firstly, it requires only a few general assumptions and can restore a high-quality haze-free image with faithful colors and fine edge details. Secondly, it benefits from a new constraint on the scene transmission, which is combined with a weighted L1-norm based contextual regularization between neighboring pixels, formalized into an optimization problem to recover the unknown transmission. Thirdly, the method is efficient and can quickly dehaze images of large sizes.

The challenges and opportunities in the practical application of dehazing techniques include the under-constrained nature of single image dehazing, the need for additional priors or constraints, and the handling of complex haze scenarios such as non-homogeneous haze or haze with varying atmospheric light.

The proposed method in the research paper addresses these challenges by deriving an inherent boundary constraint on the scene transmission, which is combined with a weighted L1-norm based contextual regularization between neighboring pixels. This approach enables the recovery of the unknown transmission and the estimation of the global atmospheric light, leading to the restoration of high-quality haze-free images with faithful colors and fine edge details.

The opportunities for future research in the field of single image dehazing include the exploration of additional priors or constraints, the handling of more complex haze scenarios, and the integration of deep learning techniques for improved performance and efficiency.

In conclusion, the practical application of dehazing techniques is crucial in various fields, and the proposed method in the research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization" provides a promising approach for restoring high-quality haze-free images with faithful colors and fine edge details. The challenges and opportunities in the field of single image dehazing highlight the need for further research and innovation to address the under-constrained nature of the problem and the handling of complex haze scenarios.

## 6.4 LIMITATIONS

The proposed method for single image dehazing in the research paper[1] has several limitations that can be further improved upon. One of the main limitations is the assumption of a homogeneous haze distribution, which may not always hold in real-world scenarios. The method may not perform well in non-homogeneous haze conditions, where the haze density varies significantly across the image.

Another limitation is the lack of consideration for the effect of different atmospheric conditions, such as varying weather and lighting conditions, on the dehazing performance. The method may not perform well in extreme weather conditions, such as heavy fog or rain, or in low light conditions.

Additionally, the method assumes that the transmission function is smooth and continuous, which may not always be the case in real-world scenarios. The method may not perform well in images with abrupt depth jumps or complex scene structures.

The method also relies on the assumption that pixels in a local image patch share a similar depth value. This assumption may not always hold, especially in images with complex scene structures or abrupt depth jumps.

Furthermore, the method does not consider the effect of color casts or shadows on the dehazing performance. The method may not perform well in images with significant color casts or shadows, which can affect the accuracy of the transmission function estimation.

Lastly, the method does not consider the effect of motion blur or camera shake on the dehazing performance. The method may not perform well in images with significant motion blur or camera shake, which can affect the accuracy of the transmission function estimation.

In conclusion, the proposed method for single image dehazing in the research paper[1] has several limitations that can be further improved upon, including the assumption of homogeneous haze distribution, the lack of consideration for different atmospheric conditions, the assumption of smooth and continuous transmission function, the reliance on the assumption of similar depth value in local image patches, and the lack of consideration for color casts, shadows, and motion blur.

# CHAPTER 7

# CONCLUSION

- **SUMMARY OF FINDINGS**
- **FUTURE PROSPECTS**

## 7.1 SUMMARY OF FINDINGS

The research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization" presents a novel method for single image dehazing that combines a boundary constraint with a weighted L1-norm based contextual regularization to estimate the unknown scene transmission. The method is based on the linear interpolation model that describes the formation of a haze image and aims to recover the scene radiance from the observed image based on this model.

The paper's main contribution is the derivation of an inherent boundary constraint on the scene transmission, which is combined with a weighted L1-norm based contextual regularization between neighboring pixels. This approach is formalized into an optimization problem to recover the unknown transmission. The method requires only a few general assumptions and can restore a high-quality haze-free image with faithful colors and fine edge details.

The paper also introduces an efficient algorithm based on variable splitting to solve the optimization problem, which enables the quick dehazing of large-sized images. The method benefits from the exploration of the boundary constraint and contextual regularization, which leads to a more efficient and accurate dehazing algorithm than existing methods.

The proposed method is evaluated on a variety of haze images, and the results demonstrate the effectiveness and efficiency of the proposed method. The method can restore high-quality haze-free images with faithful colors and fine edge details, outperforming existing methods in terms of visual quality.

the research paper presents a novel method for single image dehazing that combines a boundary constraint with a weighted L1-norm based contextual regularization to estimate the unknown scene transmission. The method is based on the linear interpolation model that describes the formation of a haze image and aims to recover the scene radiance from the observed image based on this model. The method requires only a few general assumptions and can restore a high-quality haze-free image with faithful colors and fine edge details, outperforming existing methods in terms of visual quality. The proposed method is a promising approach for single image dehazing and has potential applications in various fields such as computer vision, outdoor surveillance, and autonomous driving.

## 7.2 FUTURE PROSPECTS

The research paper "Efficient Image Dehazing with Boundary Constraint and Contextual Regularization" presents a novel method for single image dehazing that combines a boundary constraint with a weighted L1-norm based contextual regularization to estimate the unknown scene transmission. The method is based on the linear interpolation model that describes the formation of a haze image and aims to recover the scene radiance from the observed image based on this model.

In terms of future prospects, the proposed method can be extended to handle more complex haze scenarios, such as non-homogeneous haze or haze with varying atmospheric light. By addressing these challenges, the proposed method can be further generalized and applied to a wider range of hazy images.

Another potential direction for future research is the integration of deep learning techniques for improved performance and efficiency. Deep learning models, such as convolutional neural networks (CNNs), have shown promising results in various computer vision tasks, including image restoration and enhancement. By combining the proposed method with deep learning techniques, it may be possible to further improve the quality of haze-free images and reduce the computational complexity of the algorithm.

In addition, the proposed method can be applied to other image enhancement tasks, such as image denoising, deblurring, and super-resolution. The proposed method's ability to handle abrupt depth jumps and bright sky regions is particularly noteworthy, making it a promising approach for these tasks.

In conclusion, the proposed method for single image dehazing has demonstrated its effectiveness and efficiency in restoring high-quality haze-free images with faithful colors and fine edge details. The method's potential for practical applications in various fields, such as computer vision, outdoor surveillance, and autonomous driving, highlights its significance and potential for future research.

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