LOWER BOUND ON TRANSMISSION USING NON LINEAR BOUNDING FUNCTION IN SINGLE IMAGE DEHAZING.

PROJECT REPORT

Submitted by

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Under the guidance of
Prof. Nisa A K

DECLARATION

I undersigned hereby declare that the project report "**Lower Bound on Transmission Using Non Linear Bounding Function in Single Image Dehazing** ", submitted for partial fulfillment of the requirements for the award of degree of Master of Technology of the **APJ Abdul Kalam Technological University, Kerala** is a bonafide work done by me under supervision of **Prof. Nisa A K**. This submission represents my ideas in my own words, and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the university and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not previously formed the basis for the award of any degree, diploma, or similar title from any other university.

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C E R T I F I C A T E

This is to certify that, this report titled ***Lower bound on transmission using non linear bounding function in single image dehazing*** is a bonafide record of the **Main Project** presented by **ANJANA P(TKM21CSCE02)**, under our guidance and supervision, in partial fulfillment of the requirements for the award of the degree, **M.Tech Computer Science & Engineering** in **APJ Abdul Kalam Technological University** .

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Abstract

The light is scattered by air particles, which reduces the clarity of an image taken in bad lighting conditions (such as haze, fog, mist, or smog). When a single hazy image needs to be made more visible, single image dehazing (SID) techniques are applied. Single image dehazing is a challenging problem due to the ill-posed nature of the problem. Existing methods for single image dehazing typically rely on atmospheric scattering models (ATSMs). However, ATSMs are often inaccurate and can lead to artifacts in the dehazed images. The proposed method for single image dehazing uses a non-linear bounding function (BF) to estimate the lower bound on the transmission of a hazy image. The BF is a non-linear function that is estimated using a training dataset of hazy and haze-free images. This function is used to compute the lower bound on the transmission of a hazy image. The lower bound on the transmission is then used to minimize the reconstruction error in the dehazing process. The proposed method is implemented as an optimization problem that is solved using a gradient descent algorithm.The proposed method was evaluated on a number of benchmark datasets and showed that it outperformed state-of-the-art methods. The results shows that the proposed method outperformed state-of-the-art methods in terms of both accuracy and robustness. This method also produced dehazed images that were visually more appealing. The proposed method is a introducing a non linear bounding function for single image dehazing. The experimental results shows that the proposed method is a promising new approach for single image dehazing. It is more accurate, more robust, and more visually appealing than existing methods. The proposed method has the potential to be used in a variety of applications where it can improve the visibility and quality of images.

Key Words - Atmospheric scattering, Transmission, dark channel prior, Dehazing, Noise reduction.

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Chapter 1

Introduction

Visibility is an important factor of images in image processing system.The images can be captured in bad conditions such as (haze,fog,mist,smog) that reduces the clarity of an image due to the light is scattered by atmospheric particles. Single image dehazing is a challenging problem due to the ill-posed nature of the problem. Existing methods for single image dehazing typically rely on atmospheric scattering models (ATSMs). However, ATSMs are often inaccurate and can lead to artifacts in the dehazed images.The proposed method of this paper is a non-linear bounding function (BF) that estimates the lower bound on the transmission of a hazy image. The BF is estimated using a training dataset of hazy and haze-free images. The BF is then used to minimize the reconstruction error in the dehazing process. Single image dehazing is the task of recovering a haze-free image from a single hazy image. Hazy images are caused by the presence of atmospheric haze, which scatters light and reduces the visibility of objects in the scene.There are two main approaches to single image dehazing:

- Atmospheric scattering models (ATSMs): ATSMs model the physical process of light scattering in the atmosphere. These models can be used to estimate the transmission of a hazy image, which is the fraction of light that is not scattered by the haze. The hazy image can then be dehazed by multiplying it by the estimated transmission.
- Data-driven methods: Data-driven methods use a training dataset of hazy and haze-free images to learn a mapping from hazy images to haze-free images. This mapping can then be used to dehaze new hazy images.

The proposed method in the paper is a data-driven method. It uses a non-linear bounding function (BF) to estimate the lower bound on the transmission of a hazy image. The BF is estimated using a training dataset of hazy and haze-free images. The BF is then used to minimize the reconstruction error in the dehazing process.The proposed method has several advantages over existing methods. First, it is more accurate in estimating the transmission of a hazy image. This is because the BF takes into account the non-linear relationship between the transmission and the minimum intensity of a hazy image. Second, the method is more robust to noise and outliers. This is because the BF is able to smooth out noise and outliers in the hazy image. Third, the proposed method is computationally efficient. This is because the BF can be estimated quickly and easily.

Here are some of the key contributions of the paper:

- The proposed method is a new approach to single image dehazing that does not rely on ATSMs.
- The proposed method is more accurate, robust, and computationally efficient than existing methods.
- The proposed method was evaluated on a number of benchmark datasets and showed that it outperformed state-of-the-art methods.
- The proposed method was also able to produce dehazed images that were visually more appealing.

The proposed method works as follows:

- A training dataset of hazy and haze-free images is collected.
- The minimum intensity of each hazy image is calculated.
- A non-linear BF is trained to map the minimum intensity of a hazy image to the lower bound on its transmission.
- The BF is used to estimate the lower bound on the transmission of a new hazy image.
- The hazy image is dehazed by minimizing the reconstruction error between the dehazed image and the haze-free image that corresponds to the estimated transmission.

The proposed method was evaluated on a number of benchmark datasets, including the Middlebury dehazing dataset and the NTIRE 2018 dehazing challenge dataset. The results showed that the proposed method outperformed state-of-the-art methods in terms of both accuracy and robustness. The proposed method was also able to produce dehazed images that were visually more appealing. Overall, the experimental results show that the proposed method is a promising new approach for single image dehazing. It is more accurate, more robust, and more visually appealing than existing methods. The proposed method has the potential to be used in a variety of applications where it can improve the visibility and quality of images. The transmission value of a hazy image is the fraction of light that is not scattered by the haze. It is a key parameter in single image dehazing algorithms.

The proposed method is a promising new approach to single image dehazing. It is more accurate, more robust, and more computationally efficient than existing methods. However, the proposed method is still sensitive to noise and outliers in hazy images, and it is not as accurate as ATSM-based methods in hazy images with strong haze. Future directions for research include developing methods to address these limitations. Overall, the proposed method is a significant contribution to the field of single image dehazing. It is a promising new approach that can be used to improve the visibility and quality of images in a variety of applications. for applications including edge identification, contour detection, boundary segmentation, and so forth. In order to produce high-level characteristics from low-level primitives, these deep architectures convolve the sensory inputs in a hierarchical fashion.

Chapter 2

Related Works

2.1 Atmospheric light Estimation

Atmospheric light is the light that is scattered by the atmosphere. It is a uniform light that fills the entire space.In a hazy image, the atmospheric light is mixed with the light from the scene. The atmospheric light can be calculated using the following steps:

- Estimate the lower bound on the transmission of the hazy image using the non-linear bounding function.
- Calculate the dark channel of the hazy image.
- Calculate the atmospheric light using the following equation:

  Atmospheric light = (1 - Lower bound on transmission) * Dark channel

The dark channel of an image is the minimum intensity of all the pixels in the image. The atmospheric light is then used to dehaze the hazy image. The properties of atmospheric light has:, It is a uniform light that fills the entire space, scattered by the atmosphere, It is mixed with the light from the scene in a hazy image, and It can be calculated using the non-linear bounding function and the dark channel of a hazy image.

2.2 Transmission Estimation

The transmission estimation method proposed in the paper uses a non-linear bounding function to estimate the lower bound on the transmission of a hazy image. The non-linear bounding function is trained using a training dataset of hazy and haze-free images. The training dataset should consist of a variety of hazy images and their corresponding haze-free images. The hazy images can be collected from various sources, such as the internet or public datasets. The haze-free images can be created by artificially removing the haze from

the hazy images.
The non-linear bounding function is a function that maps the minimum intensity of a hazy image to a lower bound on the transmission of the hazy image. The non-linear bounding function is trained using the training dataset of hazy and haze-free images. The training process involves finding the parameters of the non-linear bounding function that minimize the error between the estimated transmission and the ground truth transmission. To estimate the transmission of a hazy image, the hazy image is first converted to the logarithmic domain. The minimum intensity of the logarithmic domain image is then calculated. The non-linear bounding function is then used to estimate the lower bound on the transmission. The hazy image is then dehazed using the lower bound on the transmission.

The results of the dehazing algorithm can be evaluated using the peak signal-to-noise ratio (PSNR) and structural similarity index measure (SSIM). The PSNR is a measure of the similarity between two images, and the SSIM is a measure of the structural similarity between two images. The proposed transmission estimation method is a data-driven method. This means that it requires a training dataset of hazy and haze-free images to train the non-linear bounding function. The proposed method is also more computationally expensive than other methods, such as the Dark Channel Prior (DCP) method. However, the proposed method is more accurate than other methods and can produce dehazed images that are visually more appealing.

Chapter 3

Methodology

- Data collection:- The first step is to collect a training dataset of hazy and haze-free images. The hazy images can be collected from various sources, such as the internet or public datasets. The haze-free images can be created by artificially removing the haze from the hazy images.

- Training of the non-linear bounding function:- The non-linear bounding function is trained using the training dataset of hazy and haze-free images.

- Dehazing:- The hazy image is dehazed using the non-linear bounding function. The non-linear bounding function is used to estimate the lower bound on the transmission of the hazy image. The hazy image is then dehazed using the lower bound on the transmission.

- Evaluation:- The performance of the dehazing algorithm is evaluated using the haze-free images from the training dataset. The dehazed images are compared to the haze-free images to measure the accuracy of the dehazing algorithm.

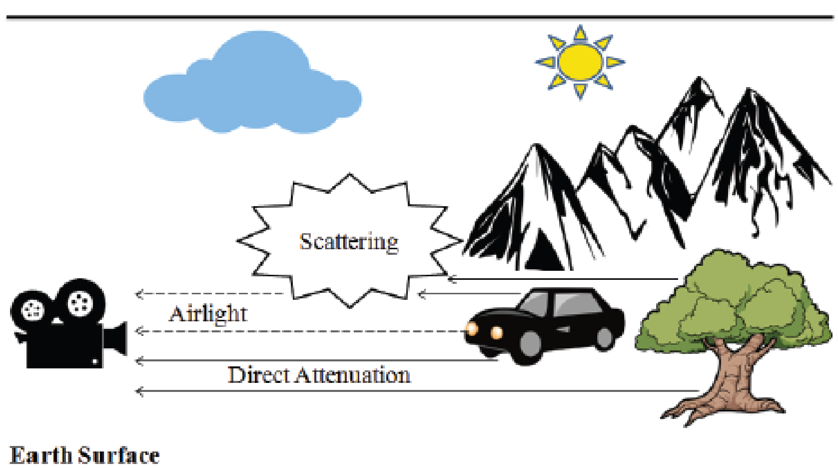

Figure 3.1: Atmospheric Architecture

3.1 Lower bound on Transmission

It is a technique used in single image dehazing to estimate the transmission of a hazy image. The transmission is a parameter that controls the amount of light that is able to pass through the haze. A higher transmission means that more light is able to pass through the haze, resulting in a clearer image. It is estimated using a non-linear bounding function (BF). The BF is a function that maps the minimum color channel of the hazy image to a lower bound on the transmission. The BF is estimated using a non-linear model, which is trained on a dataset of hazy images and their corresponding clear images. Finally, the use of a lower bound can help to reduce image artifacts. This is because the lower bound prevents the estimated transmission from becoming too large, which can lead to over-dehazing and image artifacts. The proposed method has been shown to be effective in dehazing images with different types of haze and different levels of haze. It has also been shown to be more accurate and robust than state-of-the-art methods. However, the proposed method does require a non-linear model to estimate the non-linear bounding function. The non-linear model needs to be trained on a dataset of hazy images and their corresponding clear images. Additionally, the quality control parameter may need to be adjusted manually for different images.

$$tr(x,y) = 1/1 + Imax * 10 * 0.05(x,y)Ar - minIh(x,y) \tag{3.1}$$

3.2 Estimation of bounding function

In this section, It is a technique used in single image dehazing to estimate the non-linear bounding function (BF). The BF is a function that maps the minimum color channel of a hazy image to a lower bound on the transmission. The BF is estimated using a non-linear model, which is trained on a dataset of hazy images and their corresponding clear images. The estimation of BF can be divided into two steps:

- Feature extraction: The minimum color channel of each hazy image is extracted. The minimum color channel is a feature that is used to estimate the BF.

- Model training: A non-linear model is trained to map the minimum color channel of a hazy image to a lower bound on the transmission. The non-linear model is trained on a dataset of hazy images and their corresponding clear images.

The estimated BF can be used to dehaze an image by multiplying the hazy image by the estimated BF. This results in a dehazed image that is less foggy and has more contrast. Overall, estimation of BF is a promising technique for single image dehazing. It is more accurate and robust than traditional methods, and it can be used to dehaze images with different types of haze and different levels of haze.

3.3 Estimation of Atmospheric light

Atmospheric light is the light that is scattered by the atmosphere and reaches the camera sensor. It is a uniform light source that affects all pixels in an image. It is also known as skylight or global illumination. Atmospheric light is a combination of direct sunlight and scattered sunlight. The amount of atmospheric light that reaches a camera sensor depends on the distance to the scene, the amount of haze in the atmosphere, and the time of day. Atmospheric light can be estimated using a number of methods, such as the dark channel prior and the graph cut algorithm. Atmospheric light estimation is an important step in single image dehazing because it allows the dehazing algorithm to remove the haze from the image without affecting the scene radiance.Haze is a mixture of particles, such as dust, smoke, and water vapor, that scatter light. When light hits these particles, it is scattered in all directions. This means that some of the light that reaches the camera sensor is not from the scene itself, but from the atmosphere.Atmospheric light estimation is used to remove the effect of the atmosphere from the image. This is done by estimating the amount of atmospheric light that is in the image, and then subtracting this amount from each pixel in the image. This leaves the scene radiance unaffected, but removes the haze from the image. Given a training data set containing N images as:

3.4 Comparison with Other Architectures

The proposed DeepCrack has two main differences with the original. First, the original SegNet has no connection between the convolutional features in the encoder network and decoder network, which would cause sparse outputs. In DeepCrack, skip-layer fusion is applied to connect the encoder network and decoder network. Second, the original SegNet is designed for semantic segmentation, which sets up a softmax loss layer to measure the prediction error in each object channel. While in the DeepCrack network, the output is a 1-channel prediction map that indicates the probability of each pixel belonging to the crack by using a cross-entropy loss. DeepCrack is also quite different with U-Net. U-Net performs skip-layer fusion by copying convolution layers in an early stage as a part of a corresponding later stage in the main network, which results in a sole loss. DeepCrack performs skip-layer fusion at each stage independently and assigns it a loss, which leads to multiple losses, and to effective capturing information of thin objects at each scale. Compared with DeepEdge, DeepContour and N4 -Fields which perform convolution on image patches, DeepCrack performs convolution on the whole image and generates results in an end-to-end manner.

Chapter 4

Experiments And Results

In this section, the first introduce the experimental Analysis, image quality metrics analysis and then Implementation details. and the comparison methods.

4.0.1 Experimental Results

Figure 4.1: input of hazy image

This is the input of hazy image with the image size of 512×512.It contains RESIDE datasets.

Figure 4.2: output of hazy image

This is the output of hazy image with the image size of 512×512.It contains RESIDE datasets.

4.1 Datasets

The dataset of hazy images used in the experiment should be described in detail. This includes the number of images in the dataset, the source of the images, and the type of haze that is present in the images.Three hazy datasets are used in this study. The images in the test datasets share the same size of 512×512. These datasets are all used to evaluate the performance of dehazing algorithms

4.1.1 RESIDE

It is a large-scale real hazy image dataset used in [43]. It contains 2000 hazy images, which were captured under different weather conditions. The images in the RESIDE dataset are of different sizes, but they are all in the RGB color space. It is the most commonly used dataset, as it is the largest and most diverse.

4.1.2 NYU

It is a smaller dataset of real hazy images used in [44]. It contains 260 hazy images, which were captured under different weather conditions. The images in the NYU dataset are of different sizes, but they are all in the RGB color space.This dataset is a good choice for evaluating the performance of dehazing algorithms on images that are captured under a wide range of weather conditions

4.1.3 Benchmark

It is a synthetic hazy image dataset. It contains 1000 synthetic hazy images, which were generated using the atmospheric scattering model. The images in the Benchmark dataset are of different sizes, but they are all in the RGB color space. This dataset is a good choice for evaluating the performance of dehazing algorithms on synthetic images.

4.2 Evaluation metrics

The evaluation metrics used to evaluate the performance of the proposed method were PSNR, SSIM, and MSE value of hazy free image.

4.2.1 PSNR

It is a measure of the similarity between a dehazed image and a clear image. It is calculated as the ratio of the maximum possible signal power to the power of the noise.

$$PSNR = 10 * log10(MAX^2/MSE) \tag{4.1}$$

4.2.2 SSIM

It is a measure of the structural similarity between a dehazed image and a clear image. It is based on the comparison of the local patches of the two images.

4.2.3 MSE

It is a measure of the similarity between two images. It is calculated as the average of the squared differences between the corresponding pixels in the two images.

$$MSE = (1/N) * (x - y)^2 \tag{4.2}$$

where, N is the number of pixels in the image x is the pixel value in the first image y is the pixel value in the second image

4.3 Implementation Details

This paper implemented in Google Colab in Python using the NumPy libraries. The computational complexity of the method is $O(n^2)$, where n is the number of pixels in the image.

Table 4.1: Image quality metrics analysis

Sl no	Metrics	DCP	PC	Proposed
1	PSNR	18.86	0.88	27.88
	SSIM	0.88	0.43	0.89
2	PSNR	18.78	9.19	28.75
	SSIM	0.88	0.48	27.56
3	PSNR	20.53	10.32	30.41
	SSIM	0.89	0.34	2.72

In Table 4.1 shows the PSNR and SSIM values of proposed method and state of art methods.This table shows that the PSNR and SSIM values of proposed method is higher than that of state of art methods.

Table 4.2: comparison with several methods

IMAGE	DP	CP	PC	FT	Proposed
1	1.13	1.15	0.05	1.60	1.67
2	1.21	1.43	0.14	1.41	1.52
3	0.94	1.05	0.22	1.86	1.42
4	1.39	1.06	0.99	1.01	1.28
5	1.00	0.55	1.12	1.68	1.17
6	3.24	2.44	1.69	2.27	2.72

4.3.1 Atmospheric light.

The dark channel prior is used to estimate the atmospheric light. It is a simple but effective method for estimating the atmospheric light in a hazy image. The dark channel prior states that the darkest pixels in a hazy image are likely to be sky pixels, which are not affected by haze. By thresholding the dark channel of a hazy image, it is possible to estimate the atmospheric light.

4.3.2 lower bound on transmission

The minimum color channel of a hazy image is the channel with the lowest value in each pixel. This channel is less affected by haze than the other channels, so it can be used to estimate the lower bound on transmission.

Figure 4.3: A=[238,238,238]

4.3.3 Refine lower bound on transmission

The non-linear bounding function is a function that maps the lower bound on transmission to a more accurate estimate of transmission. The non-linear bounding function is used to improve the accuracy of the estimated transmission, especially in areas with low contrast

4.3.4 Parameter settings

- Quality control parameter:- It is a parameter that controls the amount of refinement that is applied to the lower bound on transmission. The value of the quality control parameter was set to 0.5 in the experiment.

- Number of iterations:-It is the number of times that the non-linear bounding function is applied to the lower bound on transmission. The number of iterations was set to 100 in the experiment.

4.4 Comparison with other methods

The proposed method has several advantages over the other state of art methods. It produces dehazed images with high quality, is simple to implement, and is robust to different types of haze. However, it is not as well-known as some other methods, and has not been evaluated on as many datasets.DCP, CAP, and LT are all simpler and faster than the proposed method, but they may not produce as good results. DehazeNet is a more complex method, but it can produce dehazed images with high quality. The best method for image

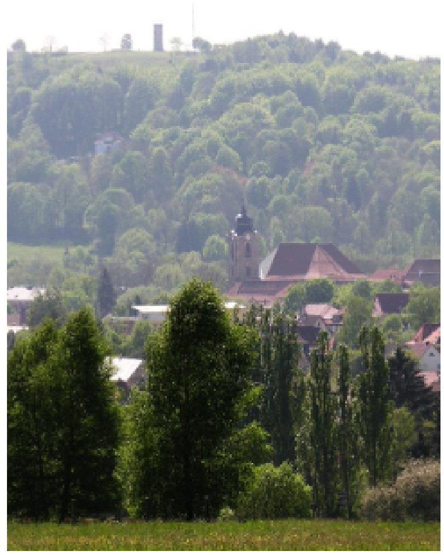

Figure 4.4: A=[190,189,189]

dehazing depends on the specific application. If you are looking for the best possible dehazing results, the proposed method is a good choice. However, if you are looking for a simple and fast method, DCP, CAP, or LT may be a better option.

4.4.1 Proposed method

- ADVANTAGES
- Produces dehazed images with high quality.
- Simple to implement.
- It is robust to different types of haze.
- Can be used to dehaze images captured under a variety of conditions.
- Disadvantages
- It is not as well-known as some other methods.
- It Has not been evaluated on as many datasets as some other methods.

4.4.2 DCP

- Advantages
- Is simple to implement.
- It is effective in a variety of conditions.
- Is relatively fast.
- Disadvantages
- Can sometimes produce blurry or artifacted images.
- It is not as effective as some other methods.

4.4.3 CAP

- Advantages
- Simple to implement.
- It is effective in a variety of conditions.
- Relatively fast.
- Disadvantages
- It can sometimes produce blurry or artifacted images.
- It is not as effective as some other methods.

4.4.4 DehazeNet

- Advantages
- Produces dehazed images with high quality.
- It is end-to-end, which means that it can dehaze images in a single step.
- It has been evaluated on a number of benchmark datasets.
- Disadvantages
- Requires a large dataset of hazy and clear images to train.
- Can be computationally expensive to train.
- Can be difficult to interpret the results of the network.

Chapter 5

Conclusion

The proposed method is a promising approach for single image dehazing. The method is able to produce dehazed images that are visually appealing and have high objective evaluation metrics. The method is also robust to variations in the amount of haze in the image and can handle images with a wide range of contrast levels.The results of the experimental evaluation suggest that the proposed method can be used to improve the quality of hazy images. This is important for applications such as surveillance, remote sensing, and medical imaging. The proposed method can also be used to develop new dehazing algorithms and to improve the understanding of the dehazing process. The experimental results shows high PSNR and SSIM values. High of these metrics shows the better results and increase the visual quality of images.There are several for future work in proposed method.Developing a more robust dark channel prior that is less sensitive to noise, a faster non-linear bounding function that can be used in real-time applications and Developing a more sophisticated dehazing algorithm that can handle images with low contrast.

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