HAZE REMOVAL AND DETAIL ENHANCEMNT ALGORITHM USING GLOBALLY GUIDED FILTERING

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE

OF

MASTER OF TECHNOLOGY
IN
INFORMATION SYSTEM

Submitted By:
Bhagyanidhi
(Roll No. - 2K16/ISY/02)

Under the supervision of
Dr.Anil Singh Parihar
Associate Professor
Department of Computer Science and Engineering
Delhi Technological University

DEPARTMENT OF INFORMATION TECHNOLOGY

DELHI TECHNOLOGICAL UNIVERSITY

SESSION: 2016-2018

CERTIFICATE

This is to certify that Ms. **BHAGYANIDHI (2K16/ISY/02)** has carried out the major project titled **"Haze Removal and Detail Enhancement Algorithm using Globally Guided Filtering"** as a partial requirement for the award of **Master of Technology** degree in **Information System** by **Delhi Technological University, Delhi.**

The Major project is a bonafide piece of work carried out (Combined globally guided filter with detail enhancement algorithm) and completed under my supervision and guidance during the academic session 2016-2018. The Matter contained in this thesis has not been submitted elsewhere for the award of any other degree.

Date:

(Project Guide)

Dr. Anil Singh Parihar

Associate Professor

Department Of Computer Science and Engineering

Delhi Technological University

DECLARATION

We hereby declare that the thesis work entitled "**Haze Removal and Detail Enhancement Algorithm using Globally Guided Filtering**" which is being submitted to Delhi Technological University, in partial fulfilment of requirements for the award of degree of Master of Technology (Information System) is a bonafide report of thesis carried out me (Combined globally guided filter with detail enhancement algorithm). The material contained in the report has not been submitted to any university or institution for the award of any degree.

Bhagyanidhi
2K16/ISY/02

ACKNOWLEDGEMENT

I express my gratitude to my major project guide **Dr. Anil Singh Parihar, Associate Professor** in **Department of Computer Science and Engineering** at **Delhi Technological University, Delhi** for the valuable support and guidance she provided in making this major project. It is my pleasure to record my sincere thanks to my respected guide for his constructive criticism and insight without which the project would not have shaped as it has.

I humbly extend my word of gratitude to Dr. Kapil Sharma, Head of Department and other faculty members of department of Information Technology for providing their valuable help and time whenever it was required.

BHAGYANIDHI

Roll No.: 2K16/ISY/02

M.Tech. (Information System)

Department of Information Technology

Delhi Technological University, Delhi

ABSTRACT

Nowadays, the utilization and demand of image filters is very high in various applications of the areas of computer vision and image processing. Many local edge preserving smoothing strategies including Guided Filter [2] and Weighted Guided Filter [3] have been proposed in the literature earlier. These have been applied for studying different applications such as detail enhancement, de-hazing, feathering and many more. But these techniques may fail to preserve fine structured regions. A new technique, i.e. globally guided filtering has been introduced for solving this issue.

In this study, I utilized the functionality of globally guided filter [1] in the de-hazing application as well as for the detail enhancement of the images. We have proposed a model for detail enhancement using globally guided filtering by incorporating edge-based weighting in it. Initially, a model was designed which was based on decomposition algorithm for detail enhancement. Then, the results are obtained for both of the algorithm models and compared. Whereas this model is having some limitation including noise amplification in flat patch areas and halo artifacts on edges. Therefore, edge-based weighting is incorporated to resolve this issue.

CONTENTS

LIST OF FIGURES

Chapter 1

INTRODUCTION

The performance of visual applications, for example, object identification and recognition relies intensely on the observation of open air common scenes. Shockingly, pictures of open air scenes are regularly debased in terrible climate conditions, for example, dimness, mist, smoke, rain, fog etc. The light is mixed with encompassing light reflected from different bearings into the line of sight by environmental constituents. The camera gets irradiance from the scene point that is weakened in the direction of line of sight due to these particles.

All things considered, the items caught under the terrible climate conditions experience the ill effects of poor contrast, fade colours, and moved luminance. It can affect the results of many computer vision and image processing applications which will have to take these hazy images as input images. De-hazing strategies can essentially enhance the contrast and improve the colour variation resulting because of these conditions. Consequently, de-hazing approaches are extensively used in different fields involving images and computer vision.

Globally guided image filtering [1] used in this study can be considered as a global edge preserving smoothing filter that can be used to achieve the two major objectives of GIF (Guided Image Filtering) and WGIF (Weighted Guided Image Filtering) which are: 1) For transferring the structure from guidance image to the image used as input image to be filtered. 2) For smoothing the image which is transferred to generate the output image.

The main difference in methodology is that it is able to achieve these objectives separately, whereas GIF [2] and WGIF [3] achieve these objectives in parallel. To achieve these objectives, this filter broadly consists of two filters which are named as global structure transfer filter and global edge preserving smoothing filter.

The structure transfer filter takes two inputs which are image needs to be filtered and a guidance vector field. Guidance vector field depicts the structure and structure transfer filter transfers this structure to the image needs to be filtered. The smoothing filter requires image to be smoothed as its first input. The second input is guidance vector field. The noteworthy point is that the WLS filter is a special case of this smoothing filter. Both these filters are described as quadratic optimisation problems.

Globally Guided filtering can be utilized for studying various applications in different areas of image processing. These applications include the haze removal, feathering, detail enhancement and many more. In this study, the de-hazing approach and detail enhancement procedure is studied using globally guided image filtering.

1.1 Motivation of Study

Due to the high demand and variety of applications, various de-hazing procedures have been introduced. This is the fact that image without haze contains more contrast than the hazy image. Depending on this fact, a de-hazing procedure [4] has been introduced which uses markov random field to maximise the contrast for recovered image. However, this technique can produce good quality outputs, but it produces over saturation in the images. In [5], the hazy image is considered using some image modelling. It also gave remarkable outputs, but it failed in case when haziness is present in image heavily.

In [6], dark channel prior is introduced. This procedure depends on the fact that various pixels of images without haze are having negligible intensity for minimum one channel. This procedure can work well also for images which have heavy haziness. Although, it can show amplification of noise in bright areas like sky areas. Depending upon the fact that there is fading of colors in hazy images and they are very bright which makes the dissimilarity level high, another procedure introduced as color attenuation prior in [2] and [6].

A linear modelling was given for representing the relation among depth and brightness using this procedure. This modelling proved to be useful for designing de-hazing procedure using GIF. The procedure in [7] works well in case of images having sky areas, it does not amplifies the noisiness. In case of images where haziness level is low, it performs well. But in case of images where haziness level is high, the quality of images after de-hazing is degraded. This procedure can be enhanced by making the coefficient values used in it dynamic rather than constant according to the level of haziness. However, this is tedious but an appreciable task to exactly finding out the values of these coefficients.

Even though, we can consider the de-hazing procedures as a special kind of detail enhancement which vary in space. However, the filtering procedures like GIF and WGIF can show over-smoothness in images, mainly for fine structured regions. Hence, these techniques can not support preservation of fine structured regions. However, these techniques can be implemented simply and have low complexity.

Other than de-hazing, the globally guided filtering can be used for studying other applications like detail enhancement, feathering and many more. This inspiration is given in [1] as the recommended future work. Hence, due to the advantages and functionalities of globally guided filtering, it inspired me to study any other application also along with the de-hazing.

1.3 *Our Contribution*

Our contribution lies in proposing a model for detail enhancement using globally guided filtering [1] by incorporating edge-based weighting in it. Initially, a model was designed which was based on decomposition algorithm for detail enhancement. Then, the results are obtained for both of the algorithm models and compared. Whereas this model is having some limitation including noise amplification in flat patch areas and halo artifacts on edges. Therefore, edge-based weighting is incorporated to resolve this issue. These models are explained in Section 3.4 and the results are shown in Section 4.2 and 4.3.

1.4 *Organization of thesis*

The thesis is organized in various chapters as follows: Chapter 2 gives an overview of the related work of the study that is what is the various research works have been done in this area and how all those work helped in evolution of our study. This includes guide image filtering, weighted guided image filtering and their limitation. Chapter 3 summarizes the research methodologies used in this thesis. This includes the globally guided image filtering, de-hazing using globally guided filtering and detail enhancement using globally guided filtering. Chapter 4 shows the results and their analysis. And at last the chapter 5 summarizes the research work under conclusion and suggests some future work.

Chapter 2

LITERATURE REVIEW

This chapter gives an overview of the research work done with relation to our thesis and is further sub divided into 2 sections i.e. guided image filtering technique and limitation of these filtering techniques. First section gives the overview of guided image filtering and second section describes the limitation of guided filter which encourages the use of globally guide filter in the de-hazing process and other applications.

2.1 Guided image filtering (GIF)

The guided filter is basically obtained from locally linear model. This filter calculates its result by taking the guidance image content into consideration. This guidance image can be same as input image and can also be other non-identical image. Similar to the well-known bilateral filter, the guided filter is also able to perform edge preserving smoothing of images. However, it performs well close to edges. Apart from smoothing, the guide filter can also perform many different tasks and can therefore be utilized in various applications. These applications include haze removal and feathering etc. The reason for these new applications is its ability for transferring the structure from guidance image to the output image.

In addition to this, the guided filter normally requires linear time complexity and hence it is a fast method. At present, it is involved in the list of quickest edge-protecting filters. Examinations demonstrate that the guided channel is both powerful and productive in an extraordinary assortment of vision and graphics applications. These applications include edge-preserving smoothing, detail enhancement, feathering, haze-removal and more.

Many applications of computer vision and image processing show a high demand of image filters. They require these filters for suppressing and extracting contents of images. There are some LTI(Linear translation invariant) filters having their explicitly defined kernels support a variety of recognition, suppression and extraction applications. As a substitution, these filters are also executed via calculating a Poisson equation and this strategy is used in a variety of image processing applications. On taking inverse of Laplacian matrix, the filters can be naturally described.

However, the guided filter is an explicitly defined filter for images. For this filter, a guidance image is taken along with the input image as input. The filter output is calculating by performing locally and linearly transformation on the guidance image. It support edge protecting smoothing applications similar to the bilateral filter. Whereas, it is not having issues of gradient reversal artifacts. As we have already considered, the guided filter has many applications apart from smoothing images. In the work done in [2], these applications of guided filter are shown with their results. The significance of guidance image is that the filter is able to produce outputs having less smoothness and more preserved structures. Additionally, the time complexity of guided filter is O(N) which shows that it has a fast processing. It does not depend on size of kernels and range of intensities.

Definition and algorithm:

The guided filter assumes that there exists a locally linear modelling for both the guidance image and filter output. Let O is the filter output and G is the guidance image. Now it assumes that the O is the result of linear transformation of guidance image G.

$$O_j = a_p G_j + b_p \text{ , } \forall j \in w_p \tag{1}$$

Here, a_p and b_p are two coefficients. The process of guided filter is illustrated in Fig. 1 [2]. It assumes that their value is constant in the window w_p. $w_p$is a squared window with radius r. This filtering makes sure that O will be having an edge when G will be having edge. This is due to the expression ∇O=a∇G. This modelling can be utilized in a variety of applications including feathering, haze removal etc.

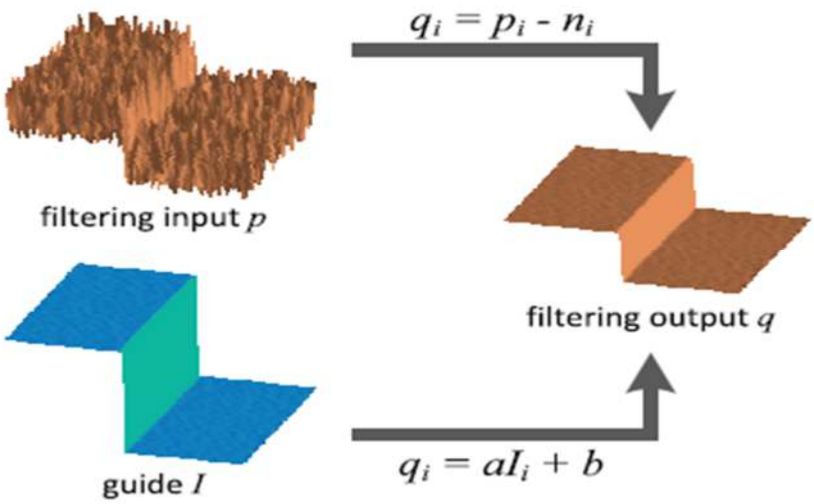


Fig. 1. Guided image filter process [2]

There are some constraints required from input image I to find the value of constants a_p and b_p. The output image O can be expressed as the subtraction of undesired constituents such as noise or textures from the input image I. This expression is shown in equation (2) below:

$$O_j = I_j - u_j \tag{2}$$

A result is required which minimise the dissimilarity of output image with input image and linear modelling should also be preserved. We can achieve this objective by minimising the cost function below in window w_p.

$$C(a_p, b_p) = \sum_{j \in w_p} \left(\left(a_p G_i + b_p - I_j \right)^2 + \epsilon {a_p}^2 \right) \tag{3}$$

Where ∈ is a regularization parameter which penalizes the larger values of a_p.

Equation (3) represents linear ridge regression model. This can be solved as follows:

$$a_p = \frac{\frac{1}{|w|} \sum_{j \epsilon w_p} G_j I_j - \mu_p \bar{I}_p}{{\sigma_p}^2 + \epsilon} \tag{4}$$

$$b_p = \bar{I}_p - a_p \mu_p \tag{5}$$

Where μ_p and σ_p represents mean and variance of guidance image G. And |w| represents how many pixels are present in w_p and $\bar{p}_p$represents mean of input image in w_p. After obtaining values of constants a_p and b_p , the filter output can be calculated using equation (1). Figure 1 demonstrates the algorithm of guided filter.

Whereas the pixel j can belong to many different overlapping windows which involve j, therefore, there will be different values for output O_j for different windows. A normal solution to this issue is by averaging all possible values of O_j. Hence, firstly values of a_p and b_p can be computed for different windows w_p for image. Then, the output image can be computed as follows:

$$O_j = \frac{1}{|w|} \sum_{p|j \in w_p} \left(a_p G_j + b_p \right) \tag{6}$$

Because the squared window is symmetrical, the expression $\sum_{p|j \in w_p} a_p = \sum_{p \in w_j} a_p$ holds true. Hence, Equation (1) can be rewritten as follows:

$$O_j = \bar{a}_j G_j + \bar{b}_j \tag{7}$$

Here, $\bar{a}_j$ and $\bar{b}_j$ are the coefficients after averaging of their values for different overlapped windows containing j. The approach of taking average is widely used in removal of noise from images and also serves as the basic term of the popular BM3D procedure.

By the improvement provided as equation (10), ∇O is now not a scale transformation of ∇G due to the reason that the coefficients a_p and b_p show variation in space. However, the coefficients a_p and b_p are the result of mean filtering, so the gradient of I is supposed to be very large as compared to gradients of these coefficients nearby stronger edges. According to this condition, the expression $\nabla O \approx a\nabla G$ still holds true. It shows that the instantaneous variation in intensity of I are almost conserved in O.

Equations (4), (5), (7) defines the guided filtering. The pseudocode for guided filter is given in algorithm 1 below.

In the following procedure, g_{mean} is the mean filter having window of radius r. And corr denotes the correlation of respective variable, var denotes variance of corresponding variable, and cov denotes covariance of referred variable. It can also be modified for quick processing and calculation.

Algorithm: Guided Filter.
Input: filter input image p, guidance image I, radius r,
regularization $\in$
Output: filter output q.
1: $mean_G = g_{mean}(G)$
$mean_I = g_{mean}(I)$
$corr_G = g_{mean}(G.* G)$
$corr_{GI} = g_{mean}(G.*I)$
2: $var_G = corr_G - mean_G * mean_G$
$cov_{Gp} = corr_{Gp} - mean_G * mean_I$
3: $a = cov_{GI} ./var_G + \in$
$b = mean_I - a .* mean_G$
4: $mean_a = g_{mean}(a)$
$mean_b = g_{mean}(b)$
5: $O = mean_a * G + mean_b$
/*g_{mean} is the mean filter from O(N) time approaches. */

Edge-preserving property:

This property ensures that the guided filter preserves edge while filtering. Now the special scenario is taken where the guidance image I is same as that of the input image p. The guided filter process the image by smoothing it while preservation of edges along with it.

The property of guided filter for preservation of edges while filtering is described here as follows. The scenario when I≈p is taken here. For the given scenario, the equations (4) and (5) can be rewritten as $a_p = {\sigma_p}^2/({\sigma_p}^2+\in)$ and $b_p = (1 - a_p)\mu_p$. Here, if we take $\in=0$, then a_p will be 1 and b_p will be 0. For value of $\in>0$, two scenarios are possible which are given as follows:

1st Scenario: Large Variance

When the guidance image show a large variation in window w_p, means $\sigma_p >> \in$, hence $a_p \approx 1$ and $b_p \approx 0$..

2nd Scenario: Very low variance

When the image I or p in nearly constant in the window, means $\sigma_p << \in$, hence $a_p \approx 0$ and $b_p \approx \mu_p$.

After averaging the values of a_p and b_p for getting $\bar{a}_i$ and $\bar{b}_i$ as given in equation (7) to produce the result, in the case of large variance the output remains same ($a_p \approx 1$, $b_p \approx 0, q \approx p$). However, in the case of very low variance, the output will be equal to the mean of neighborhood pixels ($a_p \approx 0$, $b_p \approx \mu_p, q \approx \bar{\mu}$).

In a general way it can be said that the regularization coefficient decides the scenario of whether it is in high variance or very low variance. The area where value of regularization parameter is very much greater than variance then there will be smoothing. In other case, where the value of regularization parameter is much smaller than variance then the output remains same. The regularization parameter of Guided Filtering performs like the range variance of the bilateral filter. These two terms find out whether it is a high variance area which require preservation.

Additionally, we can say that for the constant area the Guided Filtering performs the tasks of cascading with two box filters having Radius r. In other words, cascading of these filters is a nice approximate for Gaussian Filter. Hence, a relationship of Guided Filter and Bilateral Filter can be established: $r \leftrightarrow \sigma_s$ and $\in \leftrightarrow {\sigma_r}^2$. In [2], the outputs of these two filters with varying parameters are shown. The PSNR values indicate the dissimilarity between the outputs of these filters quantitatively with different set of parameter values. Normally, in the case where PSNR >= 40dB, it seems that it is not sensitive from visual results.

2.2 *Weighted Guided image filtering (WGIF)*

The techniques to smooth the image depending on local filters with edge preservation generally have a demerit of Halo Artifacts. Weighted Guided Image Filtering is basically the incorporation of weighted scheme based on edges in the pre-existing Guided Filter. This weighting Scheme solves the issue of Halo Artifacts. The WGIF incorporates the merits of global and local filters to smooth images. For instance,

1. This filtering technique has time complexity O(N) when the image has N number of pixels, that resembles the case of GIF.
2. It inherits the merit of global filters in the sense that it does not undergo Halo Artifacts.

This filtering technique has many applications in the area of image processing and computer vision. These applications include detail enhancement, image fusion, dehazing, etc. The outputs shown in [3] have good quality and it also avoids halo Artifacts in the output images. Also, the time complexity is not incremented significantly.

There is a high demand of techniques to smooth images which are able to do edge preservation in the areas of computer vision and image processing. These applications involve noise removal from images, image fusion, HDR compression, enhancement of image details, de-hazing, etc. The procedure to make images smooth generally involves decomposition of image that needs filtering to form two layers: Base Layer and Detail Layer. The base layer is produced through homogenous areas having blunt edges. The detail layer may include noise and texture. Noise can be a randomized pattern having zero average. Texture can be periodic pattern having systematic structure.

The smoothing strategies with edge preservation basically are of two kinds. First kind of filters are based on solution of global optimizing problem. The principle of performance after optimization involves one data parameter along with one regularization parameter. The data item indicates dissimilarity between the produced image and the image that needs filtering. The regularization parameter indicates the extent with which the output image has been smoothened. However, the filters depending on solution of global optimization problem leads to good quality images. But, these filters incorporates more cost of computation. Another kind is local filters which are having simple computation but they do not support preservation of blunt edges. They also suffer from Halo Artifacts along with smoothing.

As we have already considered the point that WGIF include guided filtering along with weighting based on edges. For visual quality edges give important information for recognition of objects. This weighting scheme assigns more weight to pixels on edges instead of pixels of flat patch. For calculating edge aware weights, we have various strategies.

Variance of 3×3 neighborhood of a point in guide image can be used for calculating weights. It is also possible to calculate weights through box filters corresponding to the points of guide image. The variance of neighborhood pixels normalizes the variance of given pixel in the guide image. These weights after normalization are acquired for designing WGIF. Because of this weighting scheme, the WGIF supports preservation of edges similar to any global filter. Because of this WGIF is able to avoid or reduce Halo Artifacts. Like GIF, the WGIF is able to prevent gradient reversal artifacts. Moreover, the complexity for computation of WGIF is almost equal to GIF i.e. O(N) with image having number of pixels N. The properties we discussed enable WGIF to support various applications in the areas of computer vision and image processing.

Definition:

a. Edge Aware Weighting

Assume Z is a guidance image, ${\sigma_{G,1}}^2(p')$ is the variance of guidance image for 3 × 3 neighborhood. This neighborhood is denoted by $\omega_1(p')$. Now the edge aware weighting is described with the help of variance of these neighborhood windows for every pixel which is shown below:

$$\mathrm{W}_Z(p') = \frac{1}{N}\sum_{P=1}^{N}\frac{{\sigma_{Z,1}}^2(p') + \epsilon}{{\sigma_{Z,1}}^2(p) + \epsilon} \tag{8}$$

Here, ϵ represents a constant parameter. Its value is small and it is taken as $(0.001\times \mathrm{R})^2$. Here, R denotes the dynamic range for input image. Every pixel in the guide image is utilized to compute the edge aware weighting. Additionally, the edge aware weighting provides a measure that how much a particular pixel is important in relation to the complete guidance image. Because of box filter used in [2], computation of edge aware weighting have complexity O(N) with image having N number of pixels.

Firstly, by considering the case when p' is present on edge, the evaluation result of edge aware weighting is generally greater than 1. And in the case when p' is present on smooth region, the value is generally smaller than 1.Hence, with the help of weight evaluation from equation (8), this filter assigns large weight values to edge pixels as compared to any pixel present in constant region.

However, on application of edge aware weighting, blocking issues may arise in the outputs. For avoiding these issue to come up in the outputs, Gaussian filter can be applied to smooth the weights. In the results of WGIF, it is simply shown that every edge pixel is assigned higher weight as compared to pixels of flat regions. This weighting scheme also resembles to the general property of mankind visual model that is any edge pixel has highly vital role as compared to any flat patch pixel.

One point that needs to be considered here is that there are many other strategies to assign weights to pixels along with the strategy given above. These other strategies include those obtained from gradients of Sobel and Robert. The performance of guided filter is enhanced by introducing this weighting strategy along with its main procedure.

Now, this edge aware weighting will be used as an instance for demonstration of Weighted guided image filtering. This demonstration is given in the next subsection.

b. Filtering Technique

Similar to that of GIF, the weighted guided filtering mainly assumes that there exists a locally linear modelling of guide image with the resulting image of filter.
Here, Z is assumed to be guide image and Y is assumed to be the resulting image of filter. The modelling given makes sure that the output will be having edge when the guide image will have edge.

The weight evaluation criteria given in equation (8) can be included in the cost function of guided filter. Similar to the process of guided filter, here also the objective is achieved when the dissimilarity of image that needs filtering and the resulting image of filter. This can be done when the cost function is minimized which is given as follows. After minimizing this cost function, we can calculate the values of $a_{p'}$ and $b_{p'}$.

$$C(a_{p'}, b_{p'}) = \sum_{j \in w_k} \left((a_{p'} Z_i + b_{p'} - I_j)^2 + \frac{\lambda}{\mathrm{W}_Z(p')} a_p{}^2 \right) \tag{9}$$

The evaluation of $a_{p'}$ and $b_{p'}$ can be done as follows:

$$a_{p'} = \frac{\mu_{Z\odot I,\varsigma_1}(p') - \mu_{Z,\varsigma_1}(p')\mu_{I,\varsigma_1}(p')}{\sigma_{Z,\varsigma_1}{}^2(p') + \frac{\lambda}{\mathrm{W}_Z(p')}} \tag{10}$$

$$b_{p'} = \mu_{I,\varsigma_1}(p') - a_{p'}\mu_{Z,\varsigma_1}(p') \tag{11}$$

Here, ʘ represents element by element multiplication between two matrices. $\mu_{G\odot I,\varsigma_1}$, μ_{G,ς_1} and μ_{X,ς_1}represent the average values of corresponding matrices.

The resulting evaluation of output can be defined as:

$$\hat{Y}(p) = \bar{a}_p Z(p) + \bar{b}_p \tag{12}$$

Here, $\bar{a}_p$ and $\bar{b}_p$ represent average values of $a_{p'}$ and $b_{p'}$ in neighborhood. And these can be calculated as follows:

$$\bar{a}_p = \frac{1}{|\omega_{\varsigma_1}(p)|} \sum_{p' \in \omega_{\varsigma_1}(p)} a_{p'} \tag{13}$$

$$\bar{b}_p = \frac{1}{|\omega_{\varsigma_1}(p)|} \sum_{p' \in \omega_{\varsigma_1}(p)} b_{p'} \tag{14}$$

Here, $|\omega_{\varsigma_1}(p)|$ represent the number of pixels in the neighborhood $\omega_{\varsigma_1}(p)$.

To simplify the computation and reduce complexity, the assumption is made that take the input image and guidance identical. Let us take the first scenario, where the pixel p' existing on edge. Then, the evaluation of weighting of input image will be much higher than 1. The value of $a_{p'}$ computed in weighted guided filtering is nearer to 1 as compared to guided filtering.

This shows that weighted guided filtering support preservation of edges better as compared to guided filtering. Even though, the complexity is also not incremented in case of weighted guided filtering and is maintained equal to that of guided filtering which is O(N) with the image having N number of pixel points. However, ABF also support edge preservation but its complexity the disadvantage.

2.3 Limitation of Guided Image Filtering (GIF) and Weighted Guided image Filtering (WGIF)

As we have already discussed about the guided image filtering and weighted guided image filtering, the algorithm and parameters of them are clear. According to the demonstration given in [1], these two filtering techniques are studied for the application of single image de-hazing. In that demonstration, these filtering techniques are checked for different values of radius of neighborhood. This has been illustrated that on increasing the value of radius, morphologic artifacts can be decreased to an extent. Whereas, the over smoothness can be seen in the images in case of large values of radius. Both guided image filtering and weighted guided image filtering show these effects in their results.

Maximal filter can also be used in place of minimal filter in equation (30). It has been presented that morphologic artifacts can be decreased using this. But unluckily, the over smoothness can be there in this case of using maximal filter. The effect of enabling and disabling the averaging phenomenon given in equation (6) has been also studied in [1]. It has been presented that if we disable the averaging function, we can preserve the fine structure in images. Whereas, by disabling the averaging function, the morphological effects in images can be seen easily, as they will be more noticeable in this case. Therefore, these two filters often show over smoothness in images, mainly in fine structured regions. The two main reasons for this effect are high value for radius of neighborhood taken and the averaging functionality given in equation (6). But the globally guided image filtering is able to solve this issue.

Chapter 3

RESEARCH METHODOLOGY

This chapter first describes the globally guided image filtering. In the next segment, the haze removal algorithm is described which is used to get the de-hazed output image. This algorithm uses globally guided filtering for this task.

3.1 Overview of the Globally Guided Image Filtering

It is a global edge preserving smoothing filter that can be used to achieve the two major objectives of GIF (Guided Image Filtering) and WGIF (Weighted Guided Image Filtering) which are as follows:

1) For transferring the structure from guidance image to the image used as input image to be filtered.
2) For smoothing the image which is transferred to generate the output image.

The main difference in methodology is that it is able to achieve these objectives separately, whereas GIF and WGIF achieve these objectives in parallel.

To achieve these objectives, this filter broadly consists of two filters which are named as global structure transfer filter and global edge preserving smoothing filter. The structure transfer filter takes two inputs which are image needs to be filtered and a guidance vector field. Guidance vector field depicts the structure and structure transfer filter transfers this structure to the image needs to be filtered. The smoothing filter requires image to be smoothed as its first input. The second input is guidance vector field. The noteworthy point is that the WLS filter is a special case of this smoothing filter. Both these filters are described as quadratic optimisation problems. These problems can be solved by the separating method used in [13].

3.2 Globally guided filtering technique

In the overview, it has been already discussed that inputs to this filter are the image which requires filtering and guidance vector field. Guidance vector field depicts the structure.

This filter consists of two global filters. One is to transfer the structure and other is for smoothing. The structure transfer filter requires input image and guidance vector field. It transfers the structure depicted by the guidance vector field to the input image. The structure transfer filter is defined by global optimisation problem. There are two terms in the cost function. One lies in image domain and other lies in gradient domain. The former is able to measure the fidelity of output to the input image. The latter describes the output image structure. The image domain cost function is given as

$$C_1(O, I) = \sum_p \big(O(p) - I(p)\big)^2 \tag{15}$$

Where I is the image that requires filtering. The cost function C_1 (O,I) depicts that the output image is the approximation of the input image as close as possible.

Assuming that G denotes guidance vector field which can be given as G= (G^h, G^v).

The other term of cost function is given as

$$C_2(O, G) = \sum_p \|\nabla O(p) - G(p)\|^2 \tag{16}$$

Where the output image O has the gradient field ∇O. The component C_2(O,G) implies that how much the output image structure resembles the guidance vector field. The final cost function is calculated as

$$C(O) = \lambda C_1(O, I) + C(O, G) \tag{17}$$

Here, λ is a constant whose value can't be negative and its objective is to maintain a trade off balance between both the terms.

It is worth noting that

1) The cost function of [10] will be equal to the given cost function C(O) if λ value is taken as O.
2) The case when input image pixel values are zeroes, the given cost function C(O) will match the cost function given in [12].

The cost function C(O) will be written in matrix form as

$$\lambda(O - I)^T(O - I) + (D_x O - G^h)^T(D_x O - G^h) + \big(D_y O - G^v\big)^T\big(D_y O - G^v\big) \tag{18}$$

Where the matrices D_x and D_y represent discrete differentiation operators.

The vector O which will minimize this cost function can be given by solving the following linear equation

$$\left(\lambda I + {D_x}^T D_x + {D_y}^T D_y\right) O = \lambda X + {D_x}^T G^h + {D_y}^T G^v \tag{19}$$

Here, I denotes identity matrix. We can easily show the matrix $\left(\lambda I + {D_x}^T D_x + {D_y}^T D_y\right)$ as a non-singular matrix, λ being positive whereas matrix $({D_x}^T D_x + {D_y}^T D_y)$ as singular matrix. Hence, separating approach can be applied to solve this linear equation because the matrix $\left(\lambda I + {D_x}^T D_x + {D_y}^T D_y\right)$ is a non-singular matrix in the case of positive λ. In the case of λ having zero value, this separating approach cannot be applied. The reason is that the matrix $({D_x}^T D_x + {D_y}^T D_y)$ will be singular matrix in this case.

For demonstration, this structure transfer filter is applied for estimating the transmission map of hazy image. The structure transfer filter is applied to transfer the hazy image structure to simplified dark channel. However, the guidance field structure is transferred to output image through structure transfer filter, but there is a need for smoothing of output image. The quality of the dehazed image can be enhanced by smoothing the output image. For achieving this goal, output image can be disintegrated in two layers through edge-preserving smoothing filter. This edge preserving smoothing filter can be given by the following equation

$$\min_{\varphi} \sum_p \left[\left(\varphi(p) - O^*(p)\right)^2 + \gamma \left(\frac{\left(\frac{\delta\varphi(p)}{\delta x}\right)^2}{\left|G^h(p)\right|^\theta + \epsilon} + \frac{\left(\frac{\delta\varphi(p)}{\delta y}\right)^2}{|G^v(p)|^\theta + \epsilon} \right) \right] \tag{20}$$

Here, γ , θ, and ϵ denotes some constant values.

As given in equation (20) , the vector field and the image which require smoothing are two inputs for this filter. We can prove that in the case when vector filter is taken as

$$G^h(p) = \frac{\partial O^*(p)}{\partial x}; \tag{21}$$

$$G^v(p) = \frac{\partial O^*(p)}{\partial y}; \tag{22}$$

the cost function in (20) resembles the cost function of [11]. So, it can be said that the WLS filter can be seen as special case of this filter.

In the same manner, the cost function in equation (20) can be written in matrix form as

$$(\varphi - O^*)^T(\varphi - O^*) + \gamma\left(\varphi^T {D_x}^T B_x D_x \varphi + \varphi^T {D_y}^T B_y D_y \varphi\right) \tag{23}$$

Here the matrices B_x and B_y can be defined by

$$B_x = diag\left\{\frac{1}{|G^h(p)|^{\theta} + \epsilon}\right\}; \qquad B_y = diag\left\{\frac{1}{|G^v(p)|^{\theta} + \epsilon}\right\} \tag{24}$$

The vector φ which will minimize this cost function can be given by solving the following linear equation

$$\left(I + \gamma\left({D_x}^T B_x D_x + {D_y}^T B_y D_y\right)\right)\varphi = O^* \tag{25}$$

In the same manner, the separating approach as given in [13] can be applied to solve this linear equation quickly. As given in [13] , the WLS filter speed is approximately equal to the speed of GIF and WGIF. The speeds of these two filters composing globally guided filter are almost equal to the speed of fast WLS. Hence, the globally guided filter has complexity nearly double as that of the GIF and WGIF. This globally guided filter can be used in the process of haze removal from a hazy image.

3.3 Single image de-hazing using globally guided image filtering

Through the globally guided image filtering and the Koschmiedars law, an algorithm for single image de-hazing process is given in this part. The global atmospheric light Ac(c ∈ {r, g, b}) is experimentally dictated by utilizing a various leveled looking strategy in light of the quad-tree subdivision. The estimation of the transmission map t(p) can be assessed by utilizing the globally guided image filtering. At long last, the scene radiance Y(p) can be recouped.

As indicated by the Koschmiedars law [22], the hazy picture is by and large demonstrated by

$$H_c(p) = Y_c(p)t(p) + A_c\left(1 - t(p)\right) \tag{26}$$

Here c ∈ {r, g, b} denotes channel index for colors, H_c is a hazy picture, Y_c denotes image without haziness, A_c represents atmospheric light. And, t is the medium transmission depicting the part of the light that isn't scattered and achieves the camera.

Dissimilar to the process of [8], we can assume that the estimations of A_r, A_g, and A_b are assessed prior to the calculation of simplified dark channel. Luckily, this isn't the issue in utilizing the strategy in [15] to assess the estimations of Ar, Ag furthermore, Ab. It ought to be called attention to that the strategies in [2], [3], what's more, [6] are not pertinent on the grounds that the global atmospheric light is expected to evaluate prior to dark channel calculation.

A simple hazy image algorithm is designed via utilizing the simplified dark channels of H/A and Y/A. Here, H/A and Y/A represents hazy and haziness free images after normalization respectively. Assume $\widetilde{H}_m(p)$ and $\widetilde{Y}_m(p)$ are given like

$$\widetilde{H}_m(p) = min\left\{\frac{H_r(p)}{A_r}, \frac{H_g(p)}{A_g}, \frac{H_b(p)}{A_b}\right\} \tag{27}$$

$$\widetilde{Y}_m(p) = min\left\{\frac{Y_r(p)}{A_r}, \frac{Y_g(p)}{A_g}, \frac{Y_b(p)}{A_b}\right\} \tag{28}$$

Here, $\widetilde{H}_m$ and $\widetilde{Y}_m$ represents minimal color elements for images H/A and Y/A respectively. Because transmission map t(p) does not depend on the color channels(r, g, b), we can formulate by referring equation (26) that the relation of $\widetilde{X}_m$ and $\widetilde{Z}_m$ with each other can be defined as

$$\widetilde{H}_m(p) = \big(1 - t(p)\big) + \widetilde{Y}_m(p)t(p) \tag{29}$$

Assume $\omega_\tau(p)$ is a squared window whose center is at p and having radius τ. The simplified dark channels of the images after normalization can be given by

$$J_d^{\widetilde{Y}}(p) = \min_{p' \in \omega_\tau(\mathrm{p})} \{\widetilde{Y}_m(p')\} \tag{30}$$

$$J_d^{\widetilde{H}}(p) = \min_{p' \in \omega_\tau(\mathrm{p})} \{\widetilde{H}_m(p')\} \tag{31}$$

Here, the value for τ is selected as 7.

It can be said that the value for t(p) is generally same in the window $\omega_\tau(p)$. Hence, from equation (29), the following resulting equation can be given as

$$J_d^{\widetilde{H}}(p) = \big(1 - t(p)\big) + J_d^{\widetilde{Y}}(p)t(p) \tag{32}$$

On comparing it with the decomposing process in [8], this model given in equation (32) is able to enhance the robustness of the single image de-hazing method. For instance, it can be seen from literature review that the results of [8] show somewhat over-saturation. However, this model overcomes this demerit that will be shown in results section.

The image that need filtering is $J_d^{\tilde{H}}(p)$. The guidance vector is given by $\nabla\tilde{H}_m$. The structure transfer filter will transfer the structure of to image through

$$\min_{O}\{\lambda C_1(O, J_d^{\tilde{H}}) + C_2(O, \nabla\tilde{H}_m)\} \tag{33}$$

Here, the constant λ is taken as 1/2048 for the outputs that will be shown in results section.

Then edge preserving smoothing filter can be applied to smooth the output image O*

which can be given as

$$\min_{\varphi}\sum_{p}\left[\left(\varphi(p) - O^*(p)\right)^2 + \gamma\left(\frac{\left(\frac{\delta\varphi(p)}{\delta x}\right)^2}{\left|\frac{\partial\tilde{H}_m(p)}{\partial x}\right|^{\theta} + \epsilon} + \frac{\left(\frac{\delta\varphi(p)}{\delta y}\right)^2}{\left|\frac{\partial\tilde{H}_m(p)}{\partial y}\right|^{\theta} + \epsilon}\right)\right] \tag{34}$$

Here, constants γ, θ, ϵ have their values taken as 2048, 13/8, and 1/64 respectively for the outputs which will be shown in the results section.

The optimal estimation for the transmission map can be thus calculated as

$$t^*(p) = 1 - \varphi^*(p) \tag{35}$$

In the same manner as given in [11], this approach also involves an adaptive sky-area compensation expression for distinguishing the sky area in hazy images. The estimation of evaluation of transmission map is extendedly tuned into sky area to prevent the amplification of noise in sky area.

At last, the scene radiance Y(p) is recouped as

$$Y_c(p) = \frac{H_c(p) - A_c}{t^*(p)} + A_c \tag{36}$$

3.4 Detail Enhancement using globally guided image filtering

3.4.1 Overview

Detail enhancement of images have become a prominent field in image processing. This is because it is very necessary for generating good quality images with higher detail level. In the applications like medical imaging where image details are necessary for diagnosis and detection, it has its remarkable importance.

The main objective of image detail enhancement is to enhance the way an image looks i.e. enhancing its quality and appearance. It enhances the quality detail along with staying away from other artifacts. The image detail enhancement procedures which are present usually relies on the decomposition process involving edge preservation.

According to these procedure given in [2], the input image is firstly disintegrated to form two layers. These two layers are base layer or scale and depth layer or scale. The base scale is basically the similar areas as well as the fine structured edges. The base scale can be obtained from smoothening the image along with edge preservation. The depth scale normally contains quality details and fine structures. After decomposition, the output image for detail enhancement is obtained via boosting the depth scale.

3.4.2 Model and algorithm for Detail Enhancement

The model used for algorithm of detail enhancement of images [2] is illustrated in the Fig. 2. The algorithm is explained in the following steps.

a. Computation of base scale

Suppose the input image is denoted as I. The base scale is given by the smoothening output with the edge-preservation. The base scale is denoted by Q. The base scale Q can be obtained by applying globally guided filtering which is given in Equation (20). This will give the base scale as the smoothed output with edge-preservation which will help in extraction of details from the input image. The extraction of details from the image is explained in the next step.

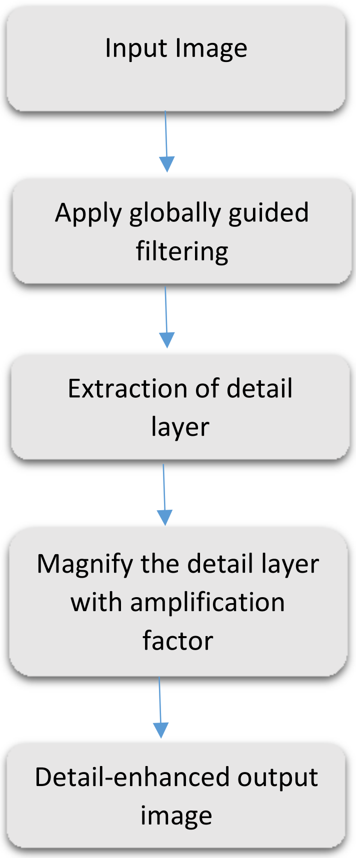


Fig. 2. Model for detail enhancement algorithm

b. Extraction of detail scale

The detail scale is given by the computing the subtraction of base scale from the input image. This will give the fine detail present within the image which is needed to be enhanced or magnified which is explained in the next step. This is shown in Equation (37). Therefore, the detail layer can be considered as

$$D = I - Q \tag{37}$$

Here, D denotes the detail scale and this Equation (37) describes the extraction of detail layer.

c. Magnify the detail layer with amplification factor

After extraction of detail scale, the detail scale is enhanced by its magnification. The detail scale can be multiplied by a positive coefficient to boost the details in the image. After this magnification, this enhanced detail scale can be added back to the input image itself. This strategy is described by Equation (38).

$$O = (I - Q) \times c + Q \tag{38}$$

Here, O represents the output image after detail enhancement and c is positive constant here. This constant c describes the extent to which detail enhancement needs to be done. Other symbols have their usual meanings already given above.

3.4.3 Limitation of above detail enhancement algorithm:

In flat patch areas, there is so much noise amplification along with enhancement of detail layer. This is because this already present algorithms enhance all the details of the given image to get the final detail-enhanced image. This has been clearly shown in the experimental results given in Section 4.2. This is actually intolerable in the case of flat patch regions. There are also halo artifacts observed near edge regions. To resolve this issue, an edge-based weighting scheme is incorporated for algorithm of detail enhancement with globally guided filtering.

3.4.4 Detail enhancement with globally guided filtering through incorporation of edge-based weighting:

The model used for enhancing details with globally guided filtering through incorporating edge-based weighting is illustrated in the Fig. 3. Afterwards, the weighting scheme is discussed.

In this model of detail enhancement, the computation of base scale and the extraction of detail scale is done in the same manner as follows. Suppose the input image is denoted as I. The base scale is given by the smoothening output with the edge-preservation. The base scale is denoted by Q. The base scale Q can be obtained by applying globally guided filtering which is given in Equation (20).The detail scale is given by the computing the subtraction of base scale from the input image. This has been shown in Equation (37).

Afterwards, edge-based weighting can be computed which is given in Equation (39). This weighting scheme depends on the local variance within the image. This incorporation of weighting is inspired by [3].This scheme show some special characteristics for different pixels i.e. for the two different cases where pixel can be either present on edges or in flat patch areas. According to this scheme, larger weights are assigned to the pixels present on edge as compared to the other pixels present in flat patch areas. These special characteristics of weighting scheme can help in resolving the issue with the previous model i.e. the issue of noise amplification in the flat patch areas and the halo artifacts near the edges. This edge-based weighting scheme is explained in the next followed section. This weighting scheme will be utilised in the magnification of details present within the image which were extracted in the previous step. All these steps for the algorithm of detail enhancement are mentioned in the flow diagram provided in the Fig. 3 shown below.

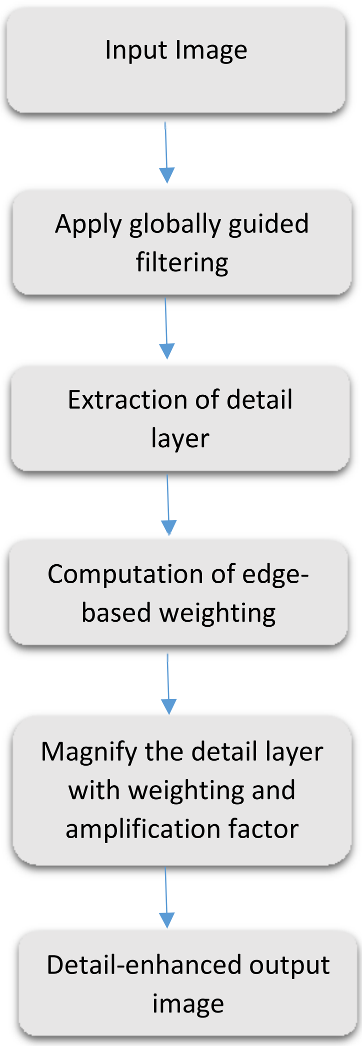


Fig. 3. Model for detail enhancement algorithm with edge-based weighting

a. Edge-based weighting

To perform the detail enhancement selectively, the following edge-based weighting scheme is incorporated. The $w(p')$ denotes the edge-base weighting for any pixel p'. The $var_1{}^2(p')$ denotes the variance of 3X3 window centred at pixel p' i.e. window with radius 1.

$$w(p') = \frac{1}{N}\sum_{p=1}^{N}\frac{var_1{}^2(p') + \varepsilon}{var_1{}^2(p) + \varepsilon} \tag{39}$$

Here, ε represents a small constant and its value is taken as $(0.001 * \mathrm{L})^2$. Where L represents the dynamic range of input image.

The evaluation of this edge-based weighting will result to more than 1 in the case when the corresponding pixel is present on edge because variance will be high in this case. The evaluation of this edge-based weighting will result to very less than 1 in the case when the corresponding pixel is present in flat patch region because variance will be very low in this case. Therefore, more weights are given to pixels on edges than in flat regions.

b. Magnification of detail layer with edge-based weighting and amplification factor

After computing this edge-based weighting for the input image, it can be incorporated in the procedure for magnification of detail scale. This is shown in the equation below.

$$O = (I - Q) \times w \times c + Q \tag{40}$$

Here, edge-based weighting w is incorporated for the magnification of detail scale. The final result after detail enhancement can be given by combining the enhanced detail scale with the base scale.

In the case when the pixel will be in flat patch region, the weighting value will be very less than 1 due to negligible variance. This behaviour is clearly shown in Equation (39). Hence, there will not be much noise amplification as that was the case in the previous algorithm. Therefore, this edge-based weighting is able to resolve the issue of noise amplification which was in the case of previous algorithm.

Chapter 4

RESULTS AND ANALYSIS

4.1 De-hazing results with globally guided filtering:

For the process of de-hazing, the globally guided filtering performs well in the terms that it supports preservation of fine structures in images. It is not show any changes in results for different values of its coefficients. The quality of de-hazed images is also good in the sense that these have appreciable sharpness. This de-hazing algorithm is also tested on the images having larger sky areas. It does not show amplification of noise in light areas.

This de-hazing algorithm relies on theories of simplified dark channel. Globally guided filter disintegerates this channel at two scales: base and detail. The base scale estimates the transmission map. Structure transfer filter is used for matching the structures of haze image and the output image as close as possible. The Fig. 4 depicts the original hazy input image. The Fig. 5 shows the output of structure transfer filter. The Fig. 6 shows the output of G-GIF after smoothening filter with edge-preservation.

Fig. 4. The original hazy image

Fig. 5. Structure transfer filter output for given image

Fig. 6. Globally guided filtering output for the given image.

Fig. 7. The input hazy image and the corrresponding de-hazed image using globally guided filtering

Afterwards, the de-hazing algorithm is applied to be tested on different kinds of input images. Here are shown some input images and their corresponding outputs for de-hazed images using globally guided filter. These kinds of input images include the images having lesss sky areas, more sky areas and images of different brightness level. The input images and their de-hazed outputs are show in the parts of Fig. 8 below.

Fig. 8. De-hazing results for other input images: The input hazy image(left) and the corrresponding de-hazed image(right) using globally guided filtering.

4.2 Detail enhancement results through globally guided filtering without edge-based weighting:

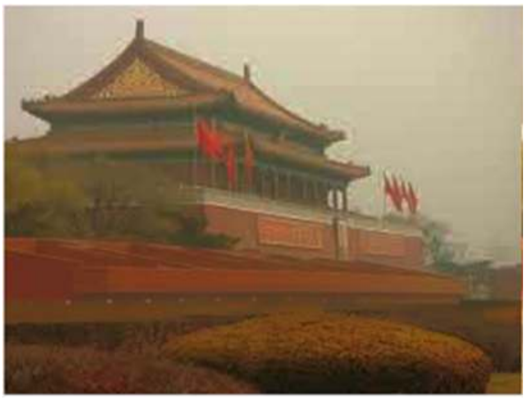
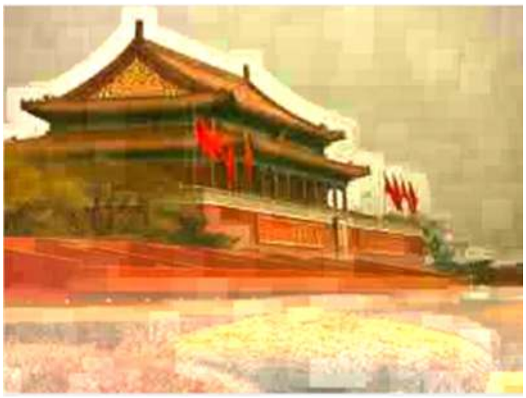
Initially, the detail enhancement of images is performed using decomposition based model and the results are obtained. This model disintegrates the given image at two scales: base scale and the detail scale. Then the detail scale undergoes magnification and added to the base scale to get the detail-enhanced image as output.

The experimental results show that in flat patch areas, there is so much noise amplification along with enhancement of detail layer. This is because this already present algorithms enhance all the details of the given image to get the final detail-enhanced image. This is actually intolerable in case of flat patch regions. There are also halo artifacts observed near edge regions. To resolve this issue, an edge-based weighting scheme is incorporated for algorithm of detail enhancement with globally guided filtering.

The parts of Fig. 9 shows the output results of detail enhancement using globally guided filtering. These results include the given input images and their corresponding output images after detail enhancement. This model for detail enhancement is applied to be tested on different kinds of input images and obtained results for them. These kinds of input images include the images having lesss sky areas, more sky areas and images of different brightness level. The input images and their detail enhanced outputs are show in the parts of Fig. 9 below.





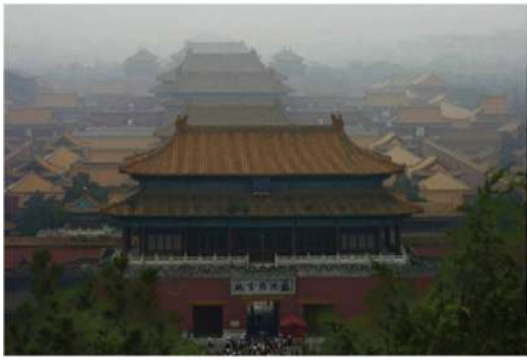
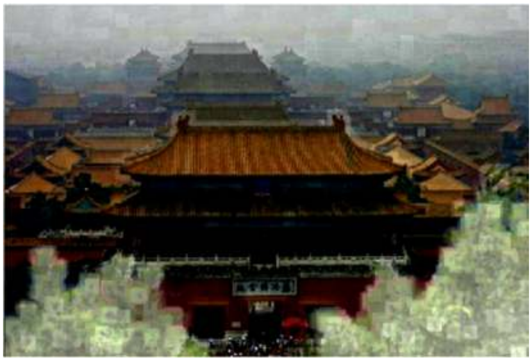
 

Fig. 9. Detail enhancement results through globally guided filtering without edge-based weighting: for other input images: The input image(left) and the corrresponding de-enhanced image(right).

4.3 Detail enhancement results through globally guided filtering with edge-based weighting:

Afterwards, detail enhancement is performed with globally guided filtering through incorporation of edge-based weighting. This is done to resolve the issue of noise amplification as was in the case of previous model for detail enhancement. The experimental results show that this model enhances the image details well in the sense that it does not show noise amplification in the flat patch areas and edges are also preserved well.

The parts of Fig. 9 shows the output results of detail enhancement using globally guided filtering. These results include the given input images and their corresponding output images after detail enhancement. This model for detail enhancement is applied to be tested on different kinds of input images and obtained results for them. These kinds of input images include the images having lesss sky areas, more sky areas and images of different brightness level. The input images and their detail enhanced outputs are show in the parts of Fig. 9 below.

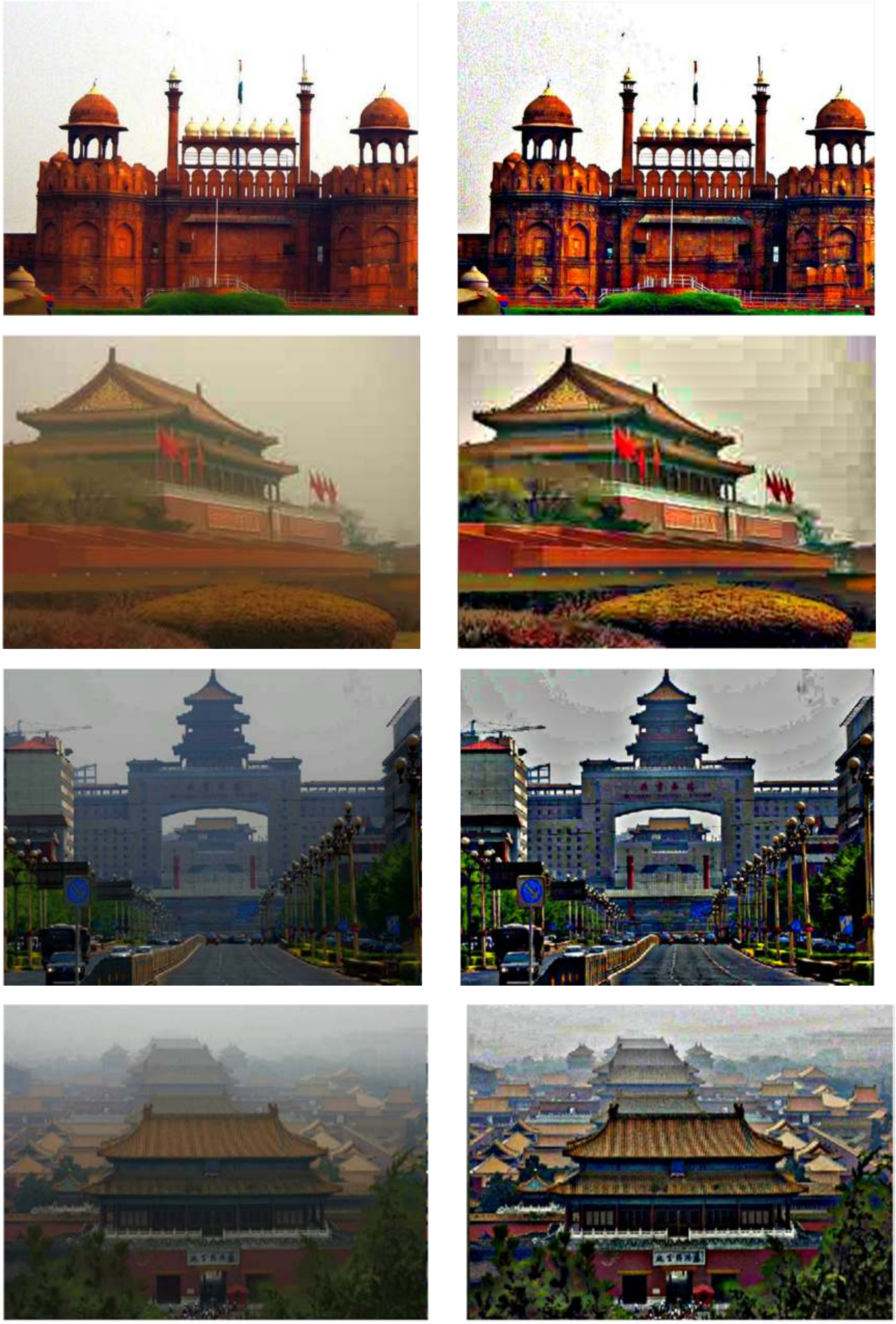


Fig. 10. Detail enhancement results through globally guided filtering with edge-based weighting: for other input images: The input image(left) and the corrresponding de-enhanced image(right).

Chapter 5

CONCLUSION AND FUTURE WORK

6.1 *Conclusion*

We can conclude that globally guided filtering technique can also be utilised to study detail enhancement of images other than de-hazing of images. For detail enhancement, we first simply used globally guided filter in the detail enhancement algorithm. However, the results of using this filter for detail enhancement are having noise amplification in the flat patch regions. To resolve this issue, we incorporated an edge-based weighting scheme in the process of detail enhancement. This scheme is able to reduce the noise amplification in flat regions and can produce good visual quality detail enhanced results. For de-hazing of images, we used globally guided filtering according to the base paper and analysed the results concluding that de-hazed images produced by using globally guided filtering are more fine structured and have appreciable sharpness.

6.2 Future Work

And as a part of the future work, the globally guided filtering technique can be further utilised to study other image processing applications apart from de-hazing and detail enhancement. These applications may include image feathering, images fusion, HDR compression etc. and then their results can be evaluated and studied.

REFERENCES

[1] Z. Li and J. Zheng, “Single Image De-Hazing Using Globally Guided Image Filtering,” *IEEE Transactions on Image Processing,* vol. 27, no. 1, pp. 442-450, 2018.

[2] K. He, J. Sun and X. Tang, “Guided Image Filtering,” *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 35, no. 6, pp. 1397-1409, 2013.

[3] Z. Li, J. Zheng, Z. Zhu, W. Yao and S. Wu, “Weighted Guided Image Filtering,” *IEEE Transactions on Image Processing,* vol. 24, no. 1, pp. 120-129, 2015.

[4] R. Tan, “Visibility in bad weather from a single image,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Anchorage, AK, USA, 2008.

[5] R. Fattal, “Single image dehazing,” in *Proc. SIGGRAPH*, New York,NY, USA, 2008.

[6] K. He, J. Sun and X. Tang, “Single image haze removal using dark channel prior,” *IEEE Trans. Pattern Anal. Mach. Intell.,* vol. 33, no. 12, p. 2341–2353, 2011.

[7] Q. Zhu, J. Mai and L. Shao, “A fast single image haze removal algorithm using color attenuation prior,” *IEEE Transactions on Image Processing,* vol. 24, no. 11, p. 3522–3533, 2015.

[8] Z. Li and J. Zheng, “Edge-preserving decomposition-based single image haze removal,” *IEEE Transactions on Image Processing,* vol. 24, no. 12, p. 5432–5441, 2015.

[9] J. Park, H. Kim, Y. W. Tai, M. S. Brown and I. Kweon, “High quality depth map upsampling for 3D-TOF cameras,” in *Proc. IEEE Int. Conf. Comput. Vis.*, Colorado Springs, CO, USA, 2011.

[10] P. Pérez, M. Gangnet and A. Blake, “Poisson image editing,” *ACM Trans. Graph,* vol. 22, no. 3, p. 313–318, 2003.

[11] Z. Farbman, R. Fattal, D. Lischinshi and R. Szeliski, “Edge-preserving decompositions for multi-scale tone and detail manipulation,” *ACM ,* vol. 27, no. 3, p. 67, 2008.

[12] J. H. Z. a. S. R. Z. G. Li, “Detail-enhanced exposure fusion,” *IEEE Transactions on Image Processing,* vol. 21, no. 11, p. 4672–4676, 2012.

[13] S. C. J. L. B. H. K. S. a. M. D. D. Min, “Fast global image smoothing based on weighted least squares,” *EEE Transactions on Image Processing,* vol. 23, no. 12, p. 5638–5653, 2014.

[14] H. Koschmider, “Theorie der horizontalen sichtweite,” *Contrib. Phys. Free Atmos.,* vol. 12, p. 171–181, 1924.

[15] W.-D. J. J.-Y. S. a. C.-S. K. J.-H. Kim, “Optimised contrast enhancement for real-time image and video dehazing,” *J. Vis. Commun. Image Represent.,* vol. 24, no. 3, p. 410–425, 2013.

[16] R. Karumuri and S. A. Kumari, “Weighted guided image filtering for image enhancement,” in *International Conference on Communication and Electronics Systems (ICCES)*, Coimbatore, 2017.

[17] W. C. Z. L. a. C. W. F. Kou, “Content Adaptive Image Detail Enhancement,” *IEEE Signal Processing Letters,* vol. 22, no. 2, pp. 211-215, 2015.

[18] Y. Tan, T. Si, G. Li and M. Xiao, “An improved detail enhancement method for colorful image via guided image,” in *IEEE International Conference on Networking, Sensing and Control*, Miami, 2014.