Day and Night-Time Dehazing by Local Airlight Estimation

03CS6901 Seminar I

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C E R T I F I C A T E

This is to certify that, this report titled ***Day and Night-Time Dehazing by Local Airlight Estimation*** is a bonafide record of the **03CS6901 Seminar I** presented on March 16, 2021 by

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Abstract

Outdoor images often suffer from poor visibility introduced by weather conditions, such as haze or fog. Haze is a common atmospheric phenomena produced by small floating particles that absorb and scatter the light from its propagation direction. Due to attenuation and scattering, hazy scenes are characterized by poor contrast of distant objects, color shifting, and additional noise. Outdoor applications such as video surveillance and automatic driving assistance require good restoration of such distorted images.In this seminar paper we discuss an effective fusion-based technique to enhance both day-time and night-time hazy scenes. When inverting the Koschmieder light transmission model, and by contrast with the common implementation of the popular darkchannel , we estimate the airlight on image patches and not on the entire image. Local airlight estimation is adopted because, under night-time conditions, the lighting generally arises from multiple localized artificial sources, and is thus intrinsically non-uniform. Selecting the sizes of the patches is, however, non-trivial. Small patches are desirable to achieve fine spatial adaptation to the atmospheric light, but large patches help improve the airlight estimation accuracy by increasing the possibility of capturing pixels with airlight appearance (due to severe haze). For this reason, multiple patch sizes are considered to generate several images, that are then merged together. The discrete Laplacian of the original image is provided as an additional input to the fusion process to reduce the glowing effect and to emphasize the finest image details. Similarly, for day-time scenes we apply the same principle but use a larger patch size. For each input, a set of weight maps are derived so as to assign higher weights to regions of high contrast, high saliency and small saturation. Finally the derived inputs and the normalized weight maps are blended in a multi-scale fashion using a Laplacian pyramid decomposition. Extensive experimental results demonstrate the effectiveness of this approach as compared with recent techniques, both in terms of computational efficiency and the quality of the outputs.

Contents

Chapter 1

Introduction

Atmospheric phenomena such as haze or fog seriously degrade the visibility of many outdoor scenes. In such bad visibility conditions, different outdoor imaging and computer vision algorithms perform poorly. To tackle this problem, many dehazing techniques have been introduced in the last decade.The earlier techniques employ additional information such as known scene depth map , or multiple images. More recently, single image-based dehazing techniques have been proposed. They generally consider the inversion of the simplified Koschmieder's optical model, and build on different priors to estimate its two unknowns, namely the transmission map and the airlight, assumed to be constant. Tan computes the airlight from the brightest pixel in the scene, and estimates the transmission by maximizing a contrast function. Based on a refined image formation model, the method of Fattal regularizes the transmission and haze color estimation by searching for a solution in which the resulting shading and transmission functions are locally statistically uncorrelated. The seminal method of He et al. introduces the dark channel prior that appeared to be a simple but effective strategy to estimate the transmission based on the observation that in natural scenes the radiance of at least one color component is very small. Meng et al.introduced a regularization method to refine the transmission estimated based on the dark channel prior, while Zhu et al. assume that the depth can be estimated from pixel saturation and intensity

While the effectiveness of these techniques has been extensively demonstrated on daylight hazy scenes, they suffer from important limitations on night-time hazy scenes.uffer from important limitations on night-time hazy scenes. Obviously, the problem of dehazing of night-time scenes is more challenging. This is mainly due to the multiple light sources that cause a strongly non-uniform illumination of the scene. As a result, the night-time dehazing problem has been addressed only by a limited number of researchers, who introduced methods specific to night-time conditions.In this seminar paper, we discuss about an effective fusion-based technique[1] to enhance the visibility of hazy scenes both in day or night conditions. The technique presented here builds on their preliminary version[2], which was specific to night dehazing. In this extended version it generalize solution to work effectively both on day and night-time hazy scenes. To the best of my knowledge, this is the first algorithm that demonstrates competitive results simultaneously on the most representative day-time and night-time dehazing datasets.

The overview of the proposed method is that, introduce a novel and general way to compute the airlight component required to invert the Koschmieder's light transmission model.Specifically, to account for non-uniform illumination,this proposed method compute this value locally, on patches of varying sizes. This is especially relevant in night-time conditions, when the lighting results from multiple artificial sources, and is thus intrinsically non-uniform.In practice, the same approach as the one recommended by the dark channel prior is adopted to estimate the airlight on each patch, based on the color of most hazy pixels, identified as brightest ones . A critical issue, however, lies in the patch size selection. Small patches are desirable to achieve fine spatial adaptation, but small patches might also lead to inaccurate airlight estimates due to the unavailability of pixels affected by strong haze when the patch becomes too small. For this reason,deploy multiple patch sizes, each generating a single input to a subsequent multi-scale fusion process.

Chapter 2

Literature survey

The quality of image taken under bad visibility is always degraded by the presence of fog, haze, smog or mist. Since the atmosphere was affected the contrast of the image is greatly reduced. Dehazing is the process of removing haze from a captured image. During the past decade many researchers have devoted on the problem of how to obtain high quality dehazed image. This section probes into several dehazing methods.
Early dehazing techniques employ additional information.For instance some techniques consider an atmospheric scattering model to derive geometric constraints on scene color changes caused by varying atmospheric conditions. They then exploit those constraints to recover the true scene colors from multiple images taken under different, but unknown, weather conditions. Other strategies use information about the 3D scene geometry. Narasimhan and Nayer [4] employ an approximated depthmap specified interactively by the users while the more recent Deep Photo system uses existing georeferenced digital terrain and urban models to restore such spoiled images.

Schechner and et al[12] [13] paper is based on the fact that usually airlight scattered by the atmospheric particles is partially polarized. The Polarization filtering alone can't remove the haze effects. This paper describes the image formation process considering the polarization effect of atmospheric scattering and inverting the process is required to get a haze free image. The image is basically composed of two unknown components, one is the scene radiance in the absence of the haze and the airlight (the ambient light scattered towards the viewer).To recover these two unknowns two independent images are required and can easily be obtained as because the airlight is usually partially polarized. This paper also describes an approach that does not need the weather conditions to change and it can be applied instantly. The images taken through a polarizer uses polarization filtering is used in photography through haze. The polarization filtering and the orientation of the polarization filter improve the contrast of the input image.

Tan[6] uses the contrast maximization techniques to remove haze from an image. He assumes that a dehazed image must have a high contrast. Tan's single image dehazing method is mostly based on two basic observations: On the one hand, the images taken under a clear weather are always with enhanced visibility and high color contrast than those taken under bad visibility like foggy weather. On the other hand, airlight whose variation mainly depends on the distance of objects to the viewer tends to be smooth. Based on these two observations and the assumption that neighboring pixels suffered from the same degradation, Tan removes the haze by maximizing the local contrast of the restored image. This method does not intend to fully recover the scene's original colors. Its purpose is to only enhance the contrast of an input image. This method only over-saturates the image visibility. Unfortunately this approach is physically invalid and makes Tan's dehazing image lacks color fidelity.Tan's method suffers from color fidelity.

Fattal[5] considers that the shading and transmission signals are uncorrelated. Based on this assumption, the airlight-albedo ambiguity can also be resolved. He used Independent Component Analysis (ICA) to estimate the transmission, and then deduct the color of the whole image by Markov Random Field (MRF). The method performs quite well for haze, but declines with scenes involving fog. This method is physically valid and capable to restore the contrasts of complex hazy scene. Moreover, since this method does not assume the haze layer to be smooth, the discontinuities in the scene depth or medium thickness are permitted. This assumption is sometime violated when the shading and transmission signals are correlated and deliver a poor dehazing result.

He et al[3] in 2009 rely on the blackbody radiation use dark channel prior approach to remove haze from an image. The blackbody theory can be understood as a theoretical object that absorbs 100% of the radiation that hits it and reflects no radiation and appears perfectly black. Namely in this case, such image's pixels are called dark pixel and their value must be very close to zero. In hazy images, the intensity of these dark pixels in that channel is mainly contributed by the air light. These dark pixels can directly provide an accurate estimation of the haze transmission. In the DCP approach soft matting method instead of MRF (Markov Random Field) is used to refine the transmission map. He et al, approach is physically valid and is able to perform with distant objects in heavily hazy images. Like any approach using a strong assumption, their approach also has its own limitation. This assumption sometime can not perform well when there is no black body in some local patches. In another way, the dark channel prior is invalid when the scene object is intrinsically the same with the air light (e.g. snowy ground or a white wall) over a large local region and no shadow is cast on it. Although their approach works well for most outdoor hazy images, but it fail on some extreme cases. This is a profitable situation because in such situations haze removal is not critical since haze is rarely visible.

Ancuti and et al.[7] described that the haze is the atmospheric phenomenon which degrades the visibility of the outdoor images captured under bad weather conditions.

This paper describes the dehazing approach for a single input image. This approach is based on the fusion strategy and it has been derived from the original hazy image inputs by applying a white balance and contrast enhancing procedure. The fusion enhancement technique estimates perceptual based qualities known as the weight maps for each pixel in the image. These weight maps control the contribution of each input to the final obtained result. Different weight maps like luminance, chromaticity and saliency are computed and to minimize the artifacts produced during the weight maps, the multiscale approach uses the laplacian pyramid representations combination with gaussian pyramids of normalized weights. As this approach tries to minimize the artifacts per pixel based has a greater improvement rather than considering a patch based method due to the assumption of contrast airlight in the patch.

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Chu and et al.[14] analysed on the concept that the degradation level that is affected by the atmospheric haze is basically dependent on the depth of the scene. Pixel in each of the part of the image tends to have the similar depth and based on these assumptions that the degradation level affected by the haze in each region is same and each pixel have the similar transmission, the given input image is segmented in to different region .After segmentation the transmission map is estimated for each region and the transmission map is refined using soft matting. The proposed method consists of five different phases such as image segmentation, atmospheric light estimation, and cost function for estimation of the transmission map. Refinement of the transmission using soft matting and lastly recovering the scene radiance. The input image is segmented in to different region using mean shift region segmentation algorithm. After the image segmentation, using dark channel prior proposed by He et al to estimate the atmospheric light. After then using the proposed algorithm the cost has been found out for the estimation of the transmission map .The transmission map is refined by applying soft matting . Then the desired haze free image is recovered by recovering the scene radiance using the dark channel prior .

Xie and et al[15] paper describes the dehazing process using dark channel prior and multi-scale retinex. This paper also focuses on the approach which provides the automatic and fast acquisition of transmission map of the scene. The proposed approach is based on the implementing the multi scale retinex algorithm on the luminance component in YCbCr space of the input image to get the pseudo transmission map .The obtained pseudo transmission map is very much similar to the transmission map obtained by using the dark channel prior by He et.al. Combining the haze imaging model and the dark channel prior, a high quality haze free image is recovered.The input hazy image has been transformed from RGB color space to YCbCr space and then by using the multiscale retinex algorithm, on the luminance component of the transformed image with some adjustment to get the transmission map. Then combining both the haze image model and the retinex algorithm a better haze free image is recovered.

Schaul and et al.[16] focused on the fact that in outdoor photography, the distant object are appeared as blurred and loses its color and visibility due to the degradation level affected by the atmospheric haze. In this paper the key idea is used to fusion of the visible and a near-infrared image of the given input image to obtain a dehazed image and it also describes the multiresolution approach using the edge preserving filter to minimize the artifacts those are produced during the dehazing process. The proposed approach describes hat from the given input hazy image both visible and near-infrared images are extracted .By applying an edge- preserving multi-resolution decomposition based on the Weighted Least Square (WLS) optimization framework as described by Farbman et al. to both visible and near- infrared images. Pixel level fusions criteria are used to maximize the contrast to improve the regions those contain the haze.

More recently, several techniques have been introduced to dehaze images captured in night-time conditions. Pei and Lee[17] estimate the airlight and the haze thickness by applying a color transfer function, before applying the dark channel prior, refined iteratively by bilateral filtering as a post-processing step. The method of Zhang et al.[18] estimates non-uniform incident illumination and performs color correction before using the dark channel prior. Santra and Chanda[19] have proposed to extend the color-line prior introduced in to deal both with day and night-time. Zhang et al.introduce a prior that is specific to night-time. The paper builds on a night-time hazy imaging model, which includes a local ambient illumination item. Then, it introduces a simple image prior, called the maximum reflectance prior, called the estimate the varying ambient illumination. In short, the prior assumes that, during night-time, the local maximum intensities of the color channels are mainly contributed by the ambient illumination. Li et al. employ an optical light transmission model augmented with an atmospheric point spread function to model the glowing effect. A spatially varying atmospheric light map is also used to estimate the transmission map, based on the dark channel prior.

Chapter 3

Dehazing by Local Airlight estimation

The method of fusion approach is accomplished in three main steps. First, based on local airlight estimation method using different patch sizes, derive the first two inputs of the fusion approach. To reduce the glowing effect and emphasize the finest details of the scene, the third input is defined to be the Laplacian of the original image. In the second step, the important features of these derived inputs are filtered based on several quality weight maps (local contrast, saturation and saliency). Finally the derived inputs and the normalized weight maps are blended in a multi-scale fashion, using a Laplacian pyramid decomposition of the inputs and a Gaussian pyramid of the normalized weights. In addition to being effective in night-time conditions, this approach appears to naturally generalize to day-time scenes, by increasing the size of the patches in response to increased contrast and a wider distribution of color in the original image.

3.1 Observation Model

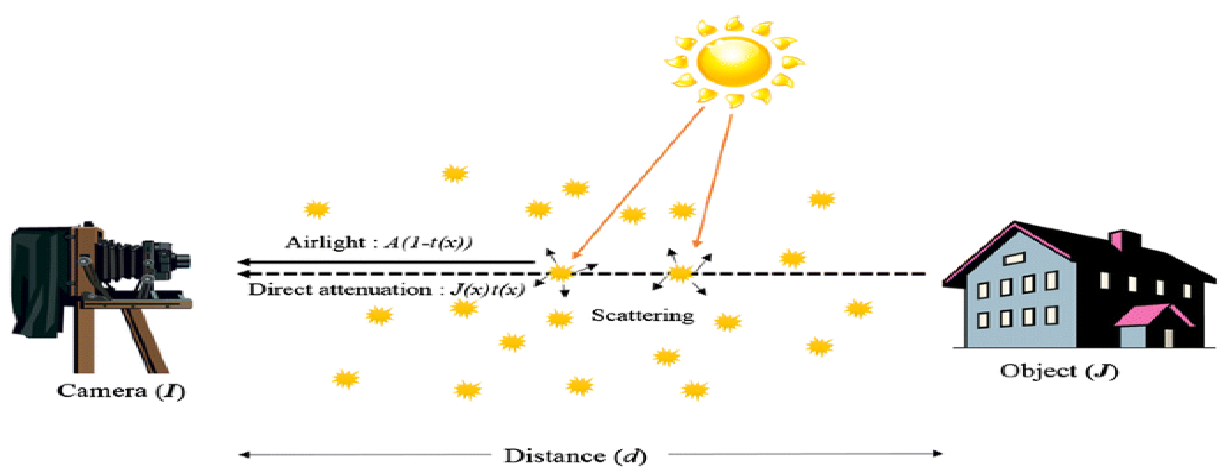

Figure 1: Observation model

The equation below is usually used to describe the formation of a foggy or hazy image where J(x) is the scene radiance or haze-free pixel color, T(x) is the transmitivity along the

$$\mathcal{I}(x) = \mathcal{D}(x) + \mathcal{A}(x) = \mathcal{J}(x)\ T(x) + A_\infty\ [1 - T(x)]\ (1)$$

cone of vision, and A is the atmospheric intensity, resulting from the environmental illumination.

The airlight A(x) is the main cause of color shifting and is expressed as:

$$\mathcal{A}(x) = A_\infty\ [1 - T(x)] \qquad (2)$$

The transmission T(x) represents the amount of light that has been transmitted between observed surface and the camera. Assuming a homogeneous medium, T(x) is approximated:

$$T(x) = e^{-\beta\ d(x)} \qquad (3)$$

where β is the medium attenuation coefficient due to scattering, and d(x) represents the distance between the camera and the physical point associated with pixel coordinate x. Practically, the dehazing problem consists in estimating the latent image J only from the hazy input image I. It is a mathematically ill-posed problem, since, in addition to J , the transmission T and the atmospheric intensity A are also unknown.

3.2 Local Airlight Estimation

3.2.1 Transmission Estimation

In Koschmieder's model, the transmission map T(x) is directly related to the distance between the observer and the considered surface (see Eq. 3) and adopting the well-known dark channel prior (DCP), T(x) can however be computed without resorting to depth estimation.

The DCP assumes that natural objects have a weak reflectance in one of the color channels (the direct radiance is small, or dark, in at least one of the R, G, B color channels), while the atmospheric intensity conveys all colors (the haze looks grey or white, i.e. all components in A are significant). Hence, assuming that A is known (we discuss estimation of it later), then T(x) can be directly estimated from the weakest color (relative to atmospheric color) over a neighborhood of x. Formally, the DCP assumption states that, in most image patches, at least one color channel has some pixels whose intensity are close to zero. It can be written as shown in figure 2:

$$\min_{y\in\Omega(x)}\left(\min_{c\in r,g,b}\mathcal{J}^c/A_\infty{}^c\right)=0 \tag{4}$$

Under this assumption, the transmission can be estimated as:

$$T(x)=1-\min_{y\in\Omega(x)}\left(\min_{c\in r,g,b}\mathcal{I}^c/A_\infty{}^c\right) \tag{5}$$

$\mathcal{I}(x)$	hazy image at image coordinate x (Eq. 1)
$\mathcal{J}(x)$	scene radiance or haze-free color image at coordinate x (Eq. 1)
$T(x)$	the transmission represents the fraction of light that has been transmitted from the scene surface to the observer (Eq. 1)
A_∞	atmospheric intensity (a global estimate) (Eq. 1)
A_∞^c	the c color component of the atmospheric light (Eq. 4)
$A_{L\infty}^c(x)$	the c color component of local atmospheric intensity within spatial neighborhoods $\Psi(x)$ around each coordinate x (Eq. 7)
$\Omega(x)$	represents a local patch centered at x (Eq. 4)
$I_{DC}(x)$	the Dark Channel estimate (Eq. 6)

Parameters and concepts used

3.2.2 Atmospheric Intensity Estimation

Early methods used to estimate the atmospheric intensity as the pixel color vector corresponding to the highest intensity in the image. This choice was motivated by the white appearance of haze in day-time scenes. Such approach could fail, typically when a white object is selected instead of a hazy pixel. To circumvent this problem, estimated the atmospheric intensity using the most haze-opaque pixels. These are defined as the ones having the brightest dark channel, i.e as the ones maximizing:

This estimator works well on day-time scenes, but suffers from two weaknesses when applied to night scenes .First, it estimates the atmospheric intensity globally over the entire picture, whereas night scenes are characterized by localized and spatially non-uniform artificial illumination. Second, by maximizing the minimum over the set of color channels, it promotes those locations taking large values in all channels. It thus implicitly assumes that the atmospheric intensity is reasonably white, which is the case in day-time scenes, but is not necessarily true for nightscenes which are often characterized by strongly colored lighting.

$$I_{DC}(x) = \min_{y\in\Omega(x)} \left(\min_{c\in r,g,b} \mathcal{I}^c(y) \right) \quad (6)$$

To address those two limitations, we propose (i) to estimate the atmospheric intensity locally, within spatial neighborhoods (x) around each coordinate x, and (ii) to independently compute each component of the atmospheric light. Formally, we define the local atmospheric intensity of color c, Ac L(x), to be:

$$A^c_{L\infty}(x) = \max_{y\in\Psi(x)} \left[\min_{z\in\Omega(y)} \left(\mathcal{I}^c(z)\right) \right] = \max_{y\in\Psi(x)} \left[I^c_{MIN}(y) \right] \quad (7)$$

To motivate this formulation,here again resort to the simplified version of the Koschmieder's optical model

$$\mathcal{I}^c(y) \approx A^c_{L\infty}(y) \cdot \rho^c(y) \cdot T(y) + A^c_{L\infty}(y)[1 - T(y)] \quad (8)$$

3.3 Fusion Process

While the above described airlight local estimation procedure significantly improves the image enhancement process, important artifacts still arise at and around patch transitions, where color shifting and glowing defects are visible. Moreover, as detailed below, the choice of the patch size appears to be delicate, potentially leading to poor quality of the output images owing to non-uniformity of the airlight in night-time scenes. To circumvent this problem, adopted a multi-scale fusion approach to merge the images obtained with different patch-sizes, thereby allowing for effective and seamless enhancement of hazy night-time images.

3.3.1 Inputs

The discussing fusion technique is a single image approach meaning that it first generates multiple inputs from the original hazy image. To do this,consider the strategy Local Airlight Estimation, but use multiple patch size to locally estimate the airlight values. In short,multiple patch sizes considered for the following reasons. The larger the patch, the more likely it will include a pixel having (close to) zero transmission, resulting in accurate airlight estimation. However, a large patch size also reduces the accuracy of spatial adjustment of the airlight, which is penalizing in the case of multiple and distinct light sources spread over the scene.In practise here considered three derived inputs :

The first input is computed using a small patch size (e.g. 20×20 for an image of size 800×600), thereby preventing estimation of the airlight from multiple light sources.

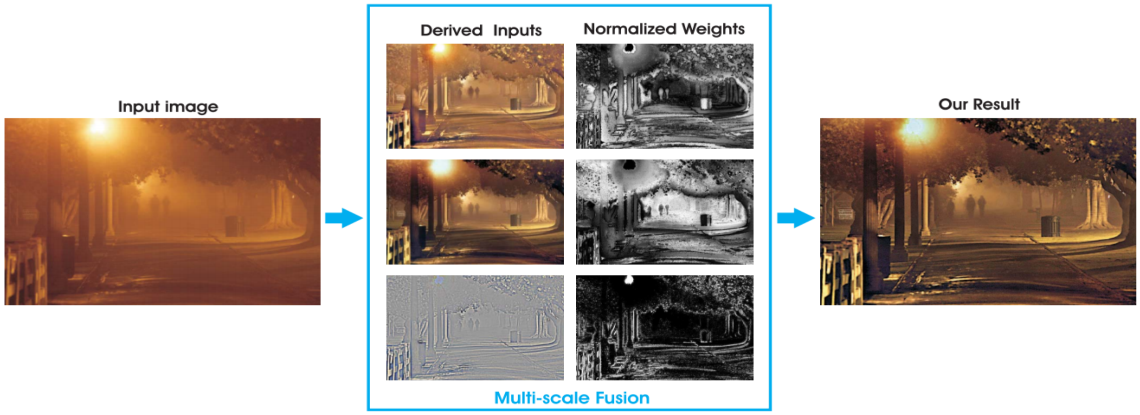

Figure 1: Multi-scale fusion of the Laplacian with images dehazed from distinct airlights, estimated on spatial neighborhoods of different sizes and the corresponding normalized weight maps.

The second input using larger patches (e.g. 80×80 for an image of size 800×600).

Third input which is the discrete Laplacian of the original image. (here we subtract from the initial image a blurred version of the image obtained using a Gaussian filter, with default standard deviation equal to two.)

This derived input considerably improves the global contrast. For completeness, we can get three observations about the generation of the two inputs. First, in practice, transitions between neighboring patches are smoothed using a simple gaussian filter. Second, as a consequence of Equation 7, when more than one light source is included in the region of interest, the airlight is estimated according to a winner-take-all strategy.Third, regarding the size of the patch, we observe that it should typically increase proportionally with the resolution of the image. This is because the impact of the patch size is primarily related to the fraction of the scene covered by the patch (a patch is considered to be small if it is likely to include a single light source, while it is considered to be large when it has a high probability of including pixels having zero transmission and, consequently, with observed color equal to airlight).To reduce such undesired effects, we derive a third input which is the discrete Laplacian of the original image. This input makes it possible to enhance the finest details that are transferred to the fused output.

3.3.2 Weight maps

Inspired by previous fusion-based dehazing approach, we derive three weight maps to ensure that regions of high contrast or of high saliency will receive greater emphasis in the fusion process[10],[11].

Local contrast weight is computed by applying a Laplacian filter to the luminance of each processed image. This indicatorestimates the amount of local variation, and has been used in applications such as tone mapping. It assigns high values to edges and texture variations.

Saturation weight map is computed as the standard deviation across channels at each coordinate. This factor is motivated by the fact that humans generally prefer images characterized by a high level of saturation.

Saliency weight map is computed as a difference between a Gaussian smoothed version of the input and its mean value, similarly to Achanta et al.. This factor highlights the most conspicuous regions of an image compared with their surroundings.

3.3.3 Multi-Scale Fusion

The main goal of the fusion process is to produce an image that smoothly blends the inputs while preserving the input features highlighted by the weight maps.In this multiscale approach, each input I is decomposed into a Laplacian pyramid while the normalized weight maps W^{-} are decomposed using a Gaussian pyramid. Using the same number of levels, the Gaussian and Laplacian pyramids, are independently fused at each level:

$$\mathcal{R}_l(x) = \sum_k G_l \left\{\bar{\mathcal{W}}^k(x)\right\} L_l \left\{\mathcal{I}_k(x)\right\} \tag{9}$$

where l represents the number of the pyramid levels, The fused result R is processed by summing the contributions from all the computed levels of the pyramid:

$$\mathcal{R}(x) = \sum_l \mathcal{R}_l(x) \uparrow^d \tag{10}$$

where , $\uparrow$ is up-scaling operator with factor d.

Chapter 4

Results

4.0.1 Dataset

In order to perform qualitative and quantitative evaluation tested this fusion approach on the recent O-HAZE dehazing dataset[20]. O-HAZE is a realistic datasets that consists of outdoor haze-free images and their corresponding hazy version, captured in the presence of real haze, generated by professional haze machines.

4.0.2 Evaluation

For quantitative evaluation, here we compute the SSIM, PSNR and CIEDE2000 INDICES between the GROUND TRUTH IMAGES and the DEHAZED IMAGES produced by the evaluated techniques for several sets of images of THE O-HAZE dataset

On closer inspection, when comparing the dehazed images with the ground truth ones, it may be observed that this technique handles color differently than other methods, leading to higher contrast and more intense colors. It also appears to improve the initial version of their method, presented in and devoted to night-time, by avoiding yellow/red color shifts. Even though this approach has the advantage of having a lower complexity compared with CNN-based solutions. But in the case of night time images this approach provide more average value in PSNR than others, Moreover this approach has the advantage of simplicity and computational efficiency.

Figure 1: Comparative results on using the day-time setting. The first row shows the hazy images and the last row shows the ground truth.

	He et al. [1]	Meng et al. [22]	Li et al. [19]	Cai et al. [4]	Ancuti et al. [20]	Ren et al. [43]	Zhang et al. [53]	Berman et al. [5]	PPDN [67]	PMS-Net [65]	Ours
SSIM	0.735	0.753	0.678	0.666	0.747	0.765	0.704	0.75	0.777	**0.814**	0.795
PSNR	16.586	17.443	15.034	16.207	16.855	19.068	17.091	16.61	**24.598**	19.045	20.159
CIEDE2000	20.745	16.968	18.211	17.348	16.431	14.67	14.816	17.088	12.124	13.467	**11.56**

Figure 2: Comparison table prepared by Authors of fusion technique based on O-HAZE dataset. (Here ours indicate the proposed fusion technique)

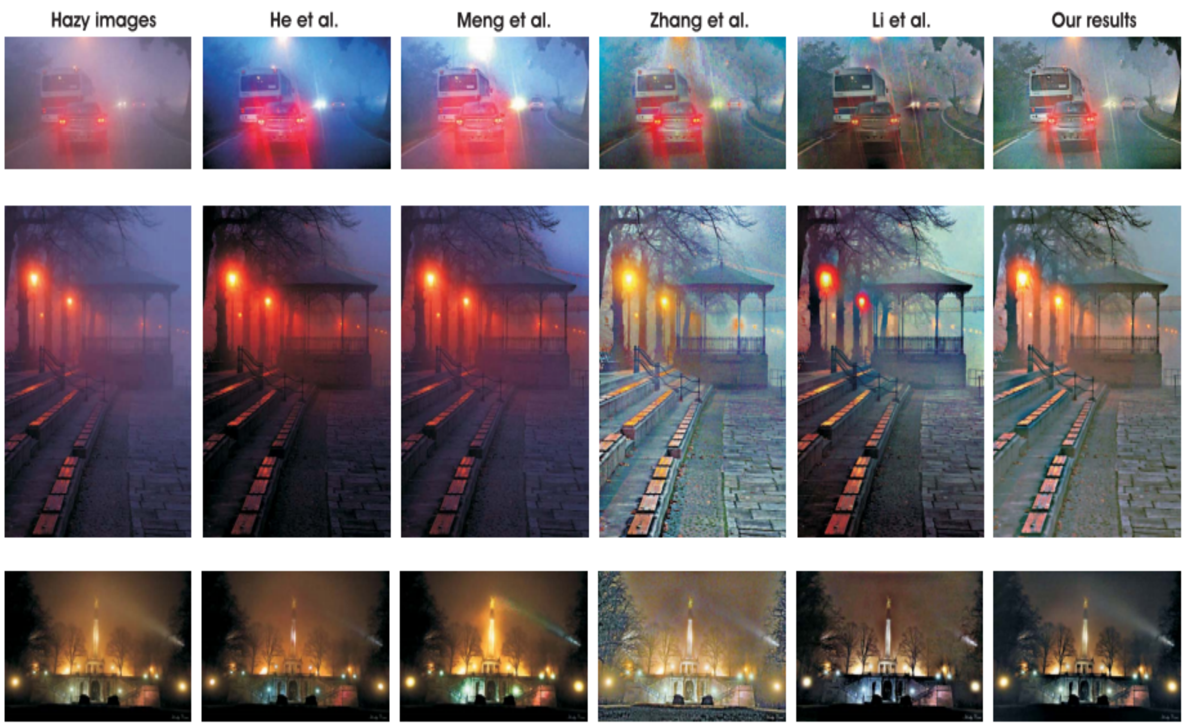

Figure 3: Comparative results for night-time hazy scenes..

Chapter 5

Conclusions

5.1 Conclusions

In this seminar paper we discussed about an effective technique to enhance both day-time and night-time hazy scenes. This mentioned method removes the haze by inverting the simplified Koschmieder's light transmission model[21]. Therefore it has to estimate the airlight. In contrast to most previous works, we estimate the airlight on local patches (and not on the whole image), since under night-time conditions, the lighting generally arises from multiple artificial sources, and is thus intrinsically nonuniform. To circumvent the patch-size selection issue, we propose to fusion multiple instances of inverted images, obtained with distinct patch sizes. An additional input, computed by a Laplace operator, is provided to the fusion process to reduce the glowing effects and emphasize the finest image details. During fusion, the derived inputs are blended in a multi-scale fashion using a Laplacian pyramid decomposition. The experimental results demonstrate the superiority of this approach compared with the recent techniques both for day and night time hazy scenes.Moreover this approach has the advantage of simplicity and computational efficiency.

5.2 Future Scope

The process of removing haze effects from images (dehazing) is an ill-posed problem.Outdoor applications such as video surveillance and automatic driving assistance are major applications where the efficient dehazing techniques needed because these require good restoration of such distorted images due to haze or other atmospheric phenomena.A single algorithm for doing dehazing in both day and night condition is not much implemented.Dehazing techniques mainly based on image enhancement ,restoration and image fusion techniques. so finding an effective dehazing methods also helps improve in these areas also. the advantage of this fusion technique is this work well for both in day and night haze scenes , even though it provide some kind of disadvantage.

References

[1] C. Ancuti, C. O. Ancuti, C. De Vleeschouwer and A. C. Bovik, ”Day and Night-Time Dehazing by Local Airlight Estimation,” in IEEE Transactions on Image Processing, vol. 29, pp. 6264-6275, 2020, doi: 10.1109/TIP.2020.2988203.

[2] C. Ancuti, C. O. Ancuti, C. De Vleeschouwer, and A. C. Bovik, “Nighttime dehazing by fusion,” in Proc. IEEE Int. Conf. Image Process. (ICIP), Sep. 2016, pp. 2256–2260.

[3] K. He, J. Sun, and X. Tang, “Single image haze removal using dark channel prior,” in Proc. IEEE CVPR, Jun. 2009, pp. 1956–1963.

[4] S.G. Narasimhan and S.K. Nayar, “Contrast restoration of weather degraded images,” IEEE Trans. on Pattern Analysis and Machine Intell., 2003.

[5] Raanan Fattal, “Single image dehazing,” SIGGRAPH, 2008

[6] Robby T. Tan, “Visibility in bad weather from a single image,” In IEEE Conference on Computer Vision and Pattern Recognition, 2008

[7] C. O. Ancuti and C. Ancuti, “Single image dehazing by multi-scale fusion,” IEEE Trans. Image Process., vol. 22, no. 8, pp. 3271–3282,Aug. 2013.

[8] J.-P. Tarel and N. Hautiere, “Fast visibility restoration from a single color or gray level image,” In IEEE ICCV, 2009.

[9] Q. Zhu, J. Mai, and L. Shao, “A fast single image haze removal algorithm using color attenuation prior,” IEEE IEEE Trans. Image Proc., 2015 Electronics-Taiwan (ICCETW),pp.1–2, 2018

[10] Mertens, J. Kautz, and F. V. Reeth, “Exposure fusion,” Comp. Graph.Forum, 2009.

[11] R. Achanta, S. Hemami, F. Estrada, and S. Susstrunk, “Frequency-tuned salient region detection,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2009, pp. 1597–1604.

[12] T. Treibitz and Y. Y. Schechner, “Polarization: Beneficial for visibility enhancement?” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit.,Jun. 2009, pp. 525–532.

[13] Y. Y. Schechner and Y. Averbuch, “Regularized image recovery in scattering media,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 29, no. 9,pp. 1655–1660, Sep. 2007.

[14] Chu, Chao-Tsung, and Ming-Sui Lee. ”A contentadaptive method for single image dehazing.” Advances in Multimedia Information Processing-PCM 2010. Springer Berlin Heidelberg, 2011. 350-361.

[15] Xie, Bin, Fan Guo, and Zixing Cai. ”Improved single image dehazing using dark channel prior and multi-scale Retinex.”Intelligent System Design and Engineering Application (ISDEA), 2010 International Conference Vol. 1. IEEE, 2010.

[16] Schaul, Lex, Clément Fredembach, and Sabine Susstrunk. ”Color image dehazing using the near-infrared.” International Conference on Image Processing (ICIP), 2009 ,16th IEEE International Conference on. IEEE, 2009.

[17] S.-C. Pei and T.-Y. Lee, “Nighttime haze removal using color transfer pre-processing and dark channel prior,” in Proc. 19th IEEE Int. Conf. Image Process., Sep. 2012, pp. 957–960.

[18] J. Zhang, Y. Cao, and Z. Wang, “Nighttime haze removal based on a new imaging model,” in Proc. IEEE Int. Conf. Image Process. (ICIP),Oct. 2014, pp. 4557–4561

[19] Santra and B. Chanda, “Day/night unconstrained image dehazing,” in Proc. 23rd Int. Conf. Pattern Recognit. (ICPR), Dec.2016,pp. 1406–1411.

[20] C. O. Ancuti, C. Ancuti, R. Timofte, and C. De Vleeschouwer,“O-HAZE: A dehazing benchmark with real hazy and haze-free outdoor images,” in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW), Jun. 2018, pp. 754–762.

[21] H. Koschmieder, “Theorie der horizontalen sichtweite,” Beitrage zur Physik der Freien Atmosphare, vol. 12, pp. 171–181, Oct. 1924.