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LOW LIGHT IMAGE DEHAZING (LLID)

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ABSTRACT

A novel method has been proposed for a single image dehazing technique to dehaze both daytime and night-time hazy scenes. Inverting the popular Koschmieder optical image formation model (KOIF) [10] with dark channel [18], the airlight on image patches is light, but large patches for accurate airlight estimation by increasing the possibility assessed and not on the entire image. Local airlight estimation is incorporated for night-time conditions with the nonuniform lighting from multiple localized artificial sources [32]. Patch Size selection is significant, small patches for fine spatial adaptation to atmospheric of capturing pixels with airlight appearance (due to severe haze). To alleviate the said problem, airlight is estimated as the brightest pixel from medium order statistic filter (MOSF) refined transmission map. The depth map is improved with the Minimum Order Statistics filter (MOSF) [37], which in turn improves the transmission map. Finally, a clear image is derived by inverting the KOIF model. The radiance is improved with a low light image enhancement technique [31]. Extensive experimental results established the effectiveness of the proposed approach as compared with recent techniques, both in terms of computational efficiency and the quality of the outputs.A novel parallel atmospheric light and depth map estimation concept has been implemented for faster operation.

Keywords- Airlight, haze, dehazing, MOSF, KOIF, Image Formation Optical Model, MOSF, PSNR, SSIM, NIQE, BRISQUE**.**

1. Introduction

In computer vision applications (object tracking and detection for autonomous driving), dehazing is a fundamental preprocessing step for the performance improvement in scenes with excessively sensitive atmospheric and illumination conditions [1, 2, 6-11, 18]. With the advent of deep learning, the performance of dehazing algorithms is showing exceptional improvements. Still, poor illumination creates dehazing algorithms that are ineffective. Hence, low-light enhancement is an additional requirement with dehazing algorithms to improve the performance of high-level vision applications. Dehazing and low-light enhancement have been studied individually in literature[31,38, 39].To conduct supervised deep learning, it is a challenge to collect training data with pairs of hazy and haze-free images of the same scenes. Moreover, the ground truth hazy images with low-light pixels are difficult to obtain. To address this challenge, a novel technique has been proposed where inverting KOIF with refined MOSF [37] depth map estimation followed by low light image enhancement [31] as shown in figure 1 with the block diagram of the

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proposed method. Hence, the proposed technique is able to clear effectively hazy images under different weather conditions. Low-light enhancement can effectively eradicate image brightness problems occurring with traditional image dehazing algorithms taking care of colour saturation problems. A novel parallel atmospheric light and depth map estimation concept has been implemented for faster operation in figure 2 which reduces computational steps saving run time. The contributions from this work are threefold: i) a unified framework for dehazing network with dehazing and low-light enhancement of images that prevents dehazed images brightness issues after removing the haze; ii) parallel estimation of atmospheric light and depth map toreduce processing cost for run time; iii) MOSF refine depth map effectively in the linear combination. The paper is organized as follows. In Section II, studies on dehazing and low light image enhancement are discussed. A new framework for dehazing with low-light enhancement is introduced in Section III. Experimental results are provided in Section IV. Discussion of the proposed method withweaknesses and future works are presented in Section V.

2. RELATED WORK

2.1. Dehazing

Dehazing techniques are the research hotspot recently. Single-image dehazing out of all dehazing techniques is gaining huge attention due to its ill-posed convex nature and large application domain where single image is the only source of information [1, 2, 6-11]. Single image dehazing Dark Channel prior (DCP) algorithm [18] shows impressive dehazing results for haze features [4, 22]. A random-forest-based regression model with multiple haze-relevant features has been employed in Tang et. al. [4]. Deep learning convolutional neural network (CNN)-based dehazing methods are found popularity in recent years [5, 21, 22, 29]. Still, non-deep learning algorithms are also being studied: in [20] haze-free images with very natural colors are developed with color-line termed as color restoration. Haze-Line also yields accurate haze-removal results in [21]. Kim et al. proposed an effective estimation of atmospheric light using quad-tree searching [40]. Chen et al. surpassed artifacts developed from dehazing using gradient residual minimization [41]. Ancuti et al. proposed a semi-inverse method and a multi-scale fusion method using multiple features for haze removal [42, 43]. In He et al. [18], the dehazing problems are mitigated with convex optimal solutions in the wavelet domain. Kim et. al. considered illumination as pixel-wise atmospheric light using the retinex theory [44]. Zhu et al. developed a new prior “color attenuation prior (CAP)” [45]. The transmission with boundary constraints and contextual regularization was estimated by Meng et. al. [19]. Choi et al. proposed a haze-measurement method for dehazing [46]. Cai et al. presented DehazeNet [29] using an end-to-end dehazing method with regression networks. Ren et al. developed coarse-to-fine multi-scale CNNs [22]. In AOD-Net [47], the atmospheric scattering model was redeveloped with an end-to-end trainable model effective for dehazing and object detection. Ling et al. developed synthetic haze images examining the light wavelength of each color channel [48]. A novel fusion method with white balancing, contrast-enhancing, and gamma correction was developed by Ren et. al. [49].

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Dense connection and pyramid modules remove hazy regions in Zhang et. al. [50]. Lately, Liu et al. developed the best quantitative results on a synthetic haze dataset [51]. Unlike the above-mentioned methods, our proposed approach performs dehazing and low-light enhancement in a unified framework based on an illumination map.

3. Methodology Applied

3.1 Low-Light Enhancement

In recent times, low light image enhancement has been studied [38]. High dynamic-range algorithms, like multi-exposure image fusion [52] and single-image contrast enhancer [53], enhance the image quality with multiple exposure images. Dong et al. inverted low-light images followed by the haze model [54]. Lately, deep learning-based methods like MSRNet [55] and LLNet [56] have attained significant improvements in low-light image enhancement algorithms. LightenNet [57] directly collects the illumination map from a convolutional neural network (CNN). In [58], the illumination is estimated indirectly using gradients and color constancy and in LIME [59], the illumination map is also used. The uniqueness of the proposed method is its fast and effective approach.

3.2 Proposed Model

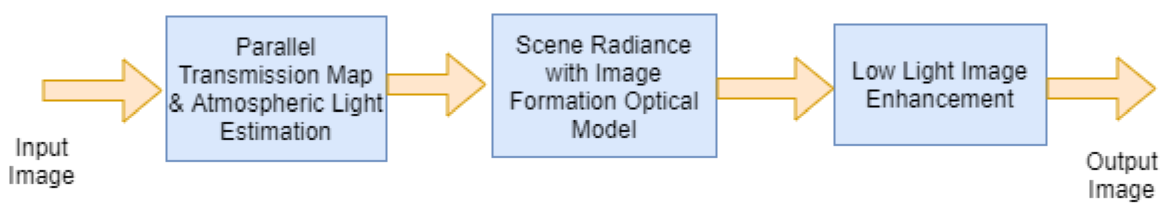

Fig. 1. Block Diagram of the Proposed Model.

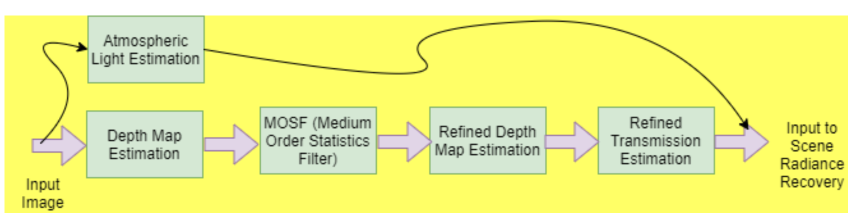

Fig. 2. Block Diagram of the Parallel Transmission and Atmospheric Light Estimation in fig. 1.

3.2.1 Proposed Method

KOIF [10] is represented as:

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$$I(x) = J(x)t(x) + A\big(1 - t(x)\big). \quad (1)$$

where I, J, A, and t define a hazy image, a haze-free image, atmospheric light, and transmission, respectively. The haze- free image is realized by solving (1) for J:

$$J(x) = \frac{I(x)-A}{t(x)} + A. \quad (2)$$

Transmission is estimated by inverting the depth map which is the minimum of three RGB channels refined by MOSF [37]. Many high-level vision tasks require a clean image on a real time basis. But in many situations, clear images may not be found on a real time basis or maybe possible with expensive installed devices. In this proposed approach, a simple and effective method has been devised without the requirement of high-end devices.

1. Depth map estimation with MOSF in KOIF model with low computational complexity O(N).
2. Parallel atmospheric light and transmission estimation reduce computational steps.
3. Low light image enhancement procedures improve weakly illuminated regions without disturbing the clearly illuminated areas from saturation and color distortion.

3.2.2 Parallel Atmospheric light and Transmission Estimation from Depth map

Atmospheric light is estimated 1% of the top [6, 7, 8, 9, 18, 37]. But this requires a separate step. To eliminate this separate step, atmospheric light is estimated while the transmission map is estimated with maximum bright pixels.

3.2.3 Scene Radiance retrieval

Scene radiance is obtained by the KOIF model [10].

3.2.4 Low Light Enhancement

The brightness of the image reduces after KOIF operation [6, 7, 8, 9, 18, 37]. This is adjusted with the low light enhancement model [31].

4. Experiment

The proposed method is implemented by MATLAB R2018a on a PC with 2.8 GHz Intel Core 2 Duo Processor. The proposed model experimented with O-Haze dataset [17], and [18] to conduct a comprehensive evaluation of the state-of-the-art single image dehazing techniques presented. In Figure 3, Qualitative results analysis for depth estimation of the proposed LLI-Dehazing. (a) Input Hazy Image, (b) MOSF image, (c) Koschmiederimage, (d) MOSF KoschmiederImage, (e) Low Light Enhanced Image. Fig. 4. shows qualitative results analysis for scene radiance estimation of the proposed LLI-Dehazing with (a) Input Hazy Image, (b) MOSF image, (c) Koschmiederimage, (d) MOSF Koschmieder Image, (e) Low Light Enhanced Image. Figure 4 illustrates one scene [18] as input with the proposed model and each step output has been extracted and compared qualitatively and quantitatively w.r.t hazy counterpart as shown in tables II. In figure 5, hazy images

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[17] is tested with Ground Truth (GT), other state-of-the-art mentors [17, 18, 19, 20, 21, 22, 29], and proposed. Its parametric evaluation is shown in table III.

4.1. Parametric Evaluator used

TABLE 1
PARAMETER USED FOREVALUATION

Sl. No.	Parameter	Requirement	Type
1	Peak Signal to Noise Ratio (PSNR) [14]	High value	Full Reference
2	Structure Similarity Index Metric (SSIM) [13]	[0-1] in normalized scale high value	Full Reference
3	blind/reference less image spatial quality evaluator (BRISQUE) [15]	Smaller value better performance	No reference
4	Naturalness Image Quality Evaluator (NIQE) [16]	Smaller value better performance	No reference

4.2Dataset:

The O-Haze dataset is used for the experiment [17]. **Day-time:Night-time:**

4.3. Results:

Fig. 3. Qualitative results analysis for depth estimation of the proposed LLI-Dehazing. (a) Input Hazy Image, (b) MOSF image, (c) Koschmieder image, (d) MOSF Koschmieder Image, (e) Low Light Enhanced Image.

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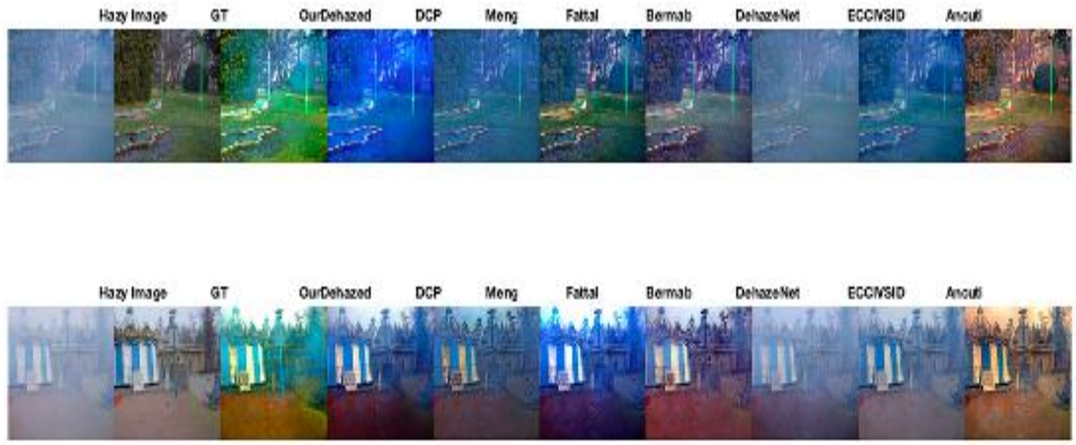

Fig. 5. Qualitative image enhancement results with two images (Top row- OHaze_13.jpg, bottom-row-OHaze_14.jpg): comparison of the proposed LLI-Dehazing and existing methods on real-world O-Haze images [17]. (a) Input underwater (dark blue, light blue, dark green, light green, shallow water, limited illumination) images, (b) He et. al. [18], (c) Meng et. al. [19], (d) Fattal [20], (e) Berman et.al. [21], (f) Cai et. al. [29]. (g) Wei et. al. [35], (h) Ancuti et. al. [36], (i) Proposed Method.

Fig. 4. Qualitative results analysis for scene radiance estimation of the proposed LLI-Dehazing. (a) Input Hazy Image, (b) MOSF image, (c) Koschmieder r image, (d) MOSF Koschmieder Image, (e) Low Light Enhanced Image.

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TABLE2

Qualitative results analysis for scene radiance estimation of the proposed LLI-Dehazing. (a) Input Hazy Image, (b) MOSF image, (c) Koschmiederimage, (d) MOSF Koschmieder Image, (e) Low Light Enhanced Image as in figure 4.

Parameter/ Image	Input Hazy Image	Depth Map	Depth Map MOSF	Scene Radiance	Depth Map (Koschmieder)	Depth Map (YCbCr)	LLIE	LLIE Depth Map
SSIM	-	-	0.9998	0.988	0.9928	0.9973	0.9954	0.9982
PSNR	-	-	26.5447	9.906	12.492	16.4841	13.5673	17.6072
NIQE	3.0904	2.8684	4.7864	3.3081	4.2252	3.8328	3.2303	3.366
BRISQUE	30.0509	20.1126	33.5485	19.2556	18.094	25.3722	23.377	28.7764

TABLE3

Quantitative comparison with state-of-the-art dehazing methods using full reference and no-reference image quality measure as in the figure. 5 (red, green, and blue as best, good, better result respectively).

		Hazy Image	GT	LLI_D	DCP	Meng	Fattal	Berman	Dehaze Net	ECCV	Ancuti
OHaze_ 13	SSIM		0.4507	0.1668	0.5042	0.6282	0.4604	0.4545	0.8626	0.8542	0.0557
	PSNR		14.8188	9.8619	10.0859	10.8753	10.2386	11.8624	16.0376	15.5725	11.5022
	NIQE	3.1426	3.8344	2.0556	2.8737	3.3225	4.3751	3.1914	2.9454	3.1535	3.4731
	BRISQUE	11.627	25.073	3.6682	17.4631	3.7697	16.0065	5.5274	9.35	21.9379	7.9659
OHaze_ 14	SSIM		0.111	0.4158	0.5352	0.8449	0.6037	0.7155	0.9911	0.8004	0.1077
	PSNR		11.4791	14.2758	12.2289	16.0505	12.247	14.3596	24.927	14.8018	12.1402
	NIQE	2.2225	2.8947	4.4892	2.7576	2.9282	2.8971	2.9447	2.3249	2.5543	3.8583
	BRISQUE	6.829	23.8179	26.9013	9.9154	14.4131	16.4514	16.4456	7.4663	15.5074	28.1483

4.4. Complexity Assessment

Computational complexity plays an important role in measuring the fast processing of an algorithm [8]. Figure 6 shows the complexity of each block of the proposed model following the total computational complexity of the model.

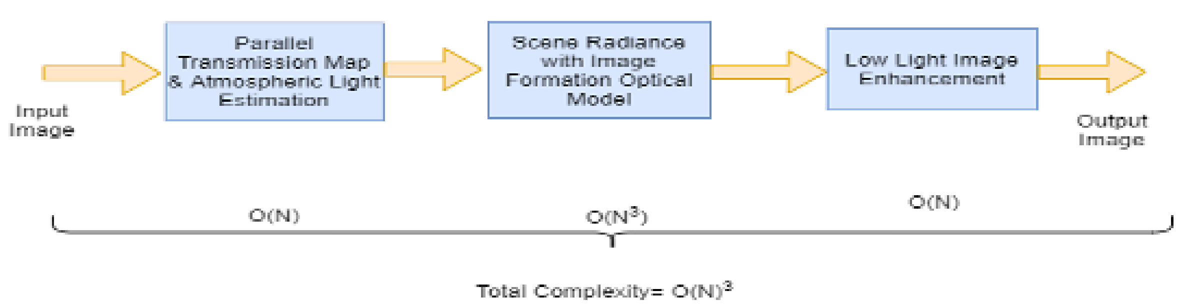

Fig. 6. Computational Complexity of the Proposed Model.

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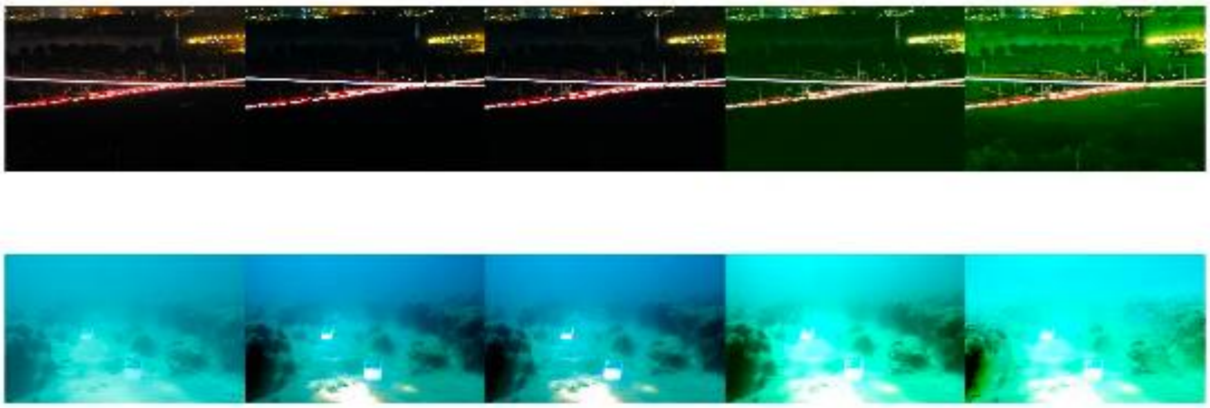

Fig. 7. a) Top Row: Nighttime dehazing, b) Bottom Roe: underwater dehazing with the proposed algorithm.

Figure 7 shows satisfactory dehazing performance with the proposed algorithm. Thus, the proposed technique can effectively improve visibility in all types of weather and illumination conditions.

5. Discussion

In this paper,an effective technique has been introducedto enhance both daytime and night-time hazy scenes.The depth map is refined through MOSF which finally improves the transmission map.In contrast to previous techniques, airlightis estimatedas the brightest pixel from the MOSF refined transmission map in parallel with depth map estimation saving extra computational steps.Inverting the KOIF [10]model, scene radiance is retrieved. To overcome the poor illumination effect, low light image enhancement has been incorporated which can be effective for day-time as well as night-time dehazing.The experimental results demonstrate the superiority of the proposedmethod compared with the recent techniques both for day and night time hazy scenes. To alleviate the said problem, airlight is estimated as the brightest pixel from the medium order statistic filter (MOSF) refined transmission map. Finally, a clear image is derived by inverting the KOIF model. The radiance is improved with a low light image enhancement technique [31]. Extensive experimental results established the effectiveness of the proposed approach as compared with recent techniques, both in terms of computational efficiency and the quality of the outputs. A novel parallel atmospheric light and depth map estimation concept has been implemented for faster operation.

Shortcomings-As the proposed model obscures original scene radiance by inverting KOIF, which is an ill-posed inverse problem with multiple results. For getting good results, much more possibilities are there.

Future scope-In the future, better results may be generated by modifying the proposed algorithmand experimenting with different path sizes of MOSF.

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