CVPR #9583

Efficient Scene Recovery Using Luminous Flux Prior

Anonymous CVPR submission

Paper ID 9583

1. Proofs

1.1. Proof on Eq. (9)

$$
\begin{aligned}
\int t \mathrm{d}t &= \int e^{-d \cdot \Delta F \cdot \mathrm{d}\beta} \\
t &= \sqrt{2e^{-d \cdot \beta \cdot \Delta F}}.
\end{aligned}
\tag{1}
$$

First, we make the following assumption: in $\int e^{-d \cdot \Delta F \cdot \mathrm{d}\beta}$, $\mathrm{d}\beta$ is considered a variable, not an infinitesimal. We denote $\mathrm{d}\beta$ as β. Then it can be written as: $\int e^{-d \cdot \Delta F \cdot \beta}$. However, this expression is still missing the integrand.

Next, we denote the entire exponent part, i.e., $-d \cdot \Delta F \cdot \beta$, as a function of β called $A(\beta)$, and integrate over $A(\beta)$, written as $\int e^{A(\beta)} \mathrm{d}A(\beta)$.

At this point, this integral is precisely a common form, which is the integral of the derivative of a function of e with respect to itself. According to the Fundamental Theorem of Calculus, the result of this integral is the function itself, which is $e^{A(\beta)}$.

Therefore, it can be deduced that $\int e^{-d \cdot \Delta F \cdot \beta} \mathrm{d}(-d \cdot \Delta F \cdot \beta) = e^{-d \cdot \Delta F \cdot \beta}$.

1.2. Proof on Eq. (12)

$$
\begin{aligned}
\lim_{\Delta F \to 0} t &= \sqrt{2F^{k \cdot \Delta F}} \\
&\approx F^{k \cdot \Delta F} \\
&\approx 1 + k \cdot \Delta F \cdot \log F
\end{aligned}
$$

The value of ΔF is the ratio of the minimum and maximum values in a sliding window. According to DCP [1], the minimum value in the sliding window is necessarily the dark channel, and the value of the dark channel is usually very small, close to 0. Therefore, $\lim_{\Delta F \to 0}$ holds true.

1Lei Zhang is the corresponding author.

1.3. Overall models

- DCP (Dark Channel Prior) [1]: DCP is a classic haze removal algorithm that utilizes the dark channel prior in an image to estimate the haze density and haze image in a scene, thereby removing haze from the image.
- MSCNN (Multi-Scale CNN) [6]: MSCNN is a multi-scale convolutional neural network model used for haze removal in images. It extracts features at different scales and combines global and local information for haze processing.
- AOD-Net (All-in-one dehazing network) [4]: AOD-Net is a deep learning-based haze removal model that estimates the atmospheric light and atmospheric light transmission in an image to remove haze and restore image clarity.
- CAP (Color Attenuation Prior) [9] formulates a linear model between depth information and the attenuation coefficient
- HRDCP (Halo-Reduced Dark Channel Prior [7]) The method first corrects color anomalies in the LAB color space using the gray world theory, then employs the Dark Channel Prior (DCP) technique for dust removal. Subsequently, it enhances contrast using a Gamma function improved Contrast Limited Adaptive Histogram Equalization (CLAHE), complemented by a guided filter for artifact mitigation.
- CVC (Chromatic Variance Consistency [2]) The method commences by executing a color correction process that safeguards chromatic variances and means, enhancing the overall image quality. It then applies a gamma correction-based dehazing technique, followed by a cross-correlation-based chromatic histogram shift, to minimize reddish artifacts, resulting in significantly improved image clarity.
- ULAP (Underwater Light Attenuation Prior) [8] The method utilizes learning-based supervised linear regression to train its coefficients, allowing for precise estimation of the depth map. This, in turn, enables straightforward calculation of the background light and transmission maps for RGB light, leading to the recovery of the true scene radiance underwater.
- Retinex [3] The Retinex method is a powerful image enhancement technique that aims to improve the perceived brightness, contrast, and color of an image. It operates on the assumption that an image can be decomposed into the product of illumination and reflectance, and works by independently modifying these components to achieve a more visually pleasing result. However, it is not specifically designed for scene recovery tasks.
- Rank One(Rank One Prior) [5] The cornerstone of the proposed method is an intensity projection strategy, driven by a simplified rank-one transmission prior, to estimate the transmission.

Table 1. We categorized the scenes targeted by each model. Hazy weather is designated as gray, sandy weather as yellow-brown, underwater environments as blue, and models applicable to all three weather conditions are designated as lightgreen.

Type	Haze				
Model Name	DCP [1]	MSCNN [6]	LDCP [10]	AOD-Net [4]	CAP [9]
Type	Sand				
Model Name	HRDCP [7]	CVC [2]			
Type	Water				
Model Name	Dive+	ULAP [8]			
Type	Full				
Model Name	retinex [3]	Rank One [5]	LFP		

2. Visualizations

2.1. Sand-Dust image enhancement

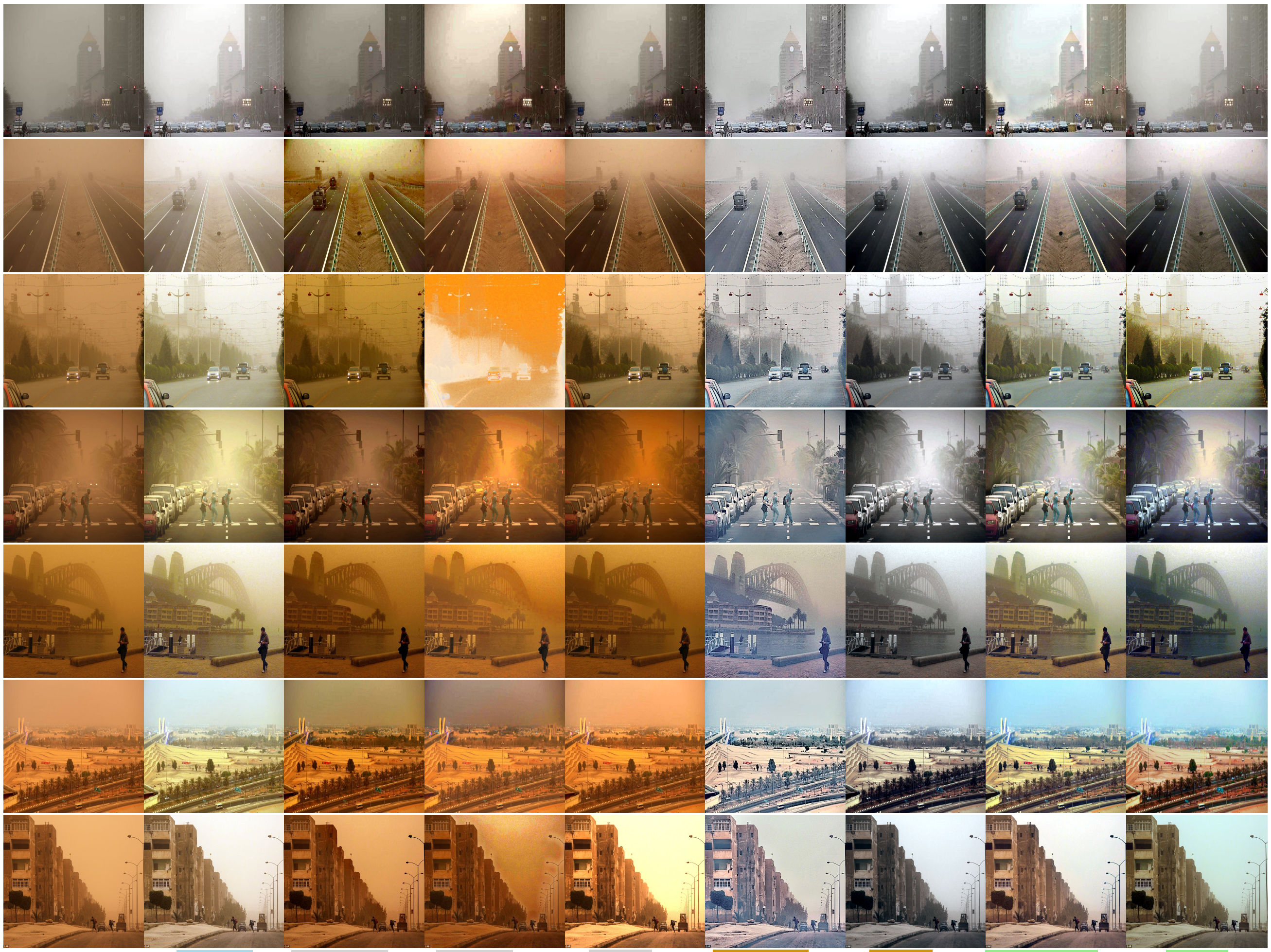


Figure 1. Sandstorm image enhancement results obtained by different methods. (The images are best viewed in the full-screen mode.)

The occurrence of sandstorms significantly reduces visibility, as floating dust and sand scatter and absorb light, creating a negative impact on practical applications. To address this issue, we have developed a novel restoration method and compared it with other common dehazing techniques such as DCP, MSCNN, and LDCP, as well as the underwater image enhancement method Dive+. The results are shown in Fig 1. Traditional dehazing methods often succeed in restoring the main structure of images, but they are not sufficiently effective in dealing with the light scattering and absorption caused by sandstorms. This is likely because these methods are primarily designed based on imaging theories for smoggy weather, and there exist differences in the imaging mechanisms between sandstorms, smoggy weather, and underwater environments. For instance, although the Retinex-based method achieves some success in restoring image quality, it still suffers from color distortion issues, such as generating an unnatural cool tone, causing inconsistent brightness, and losing texture details, thereby reducing image quality. In contrast, the LFP method demonstrates more robust performance in combating sandstorms, effectively restoring the natural colors and structure of images. This is because LFP not only restores the main structure of the images but also effectively mitigates the impact of dust and sandstorms, providing clearer and more natural image results. Therefore, LFP offers a more effective solution for dealing with the reduced visibility caused by sandstorms.

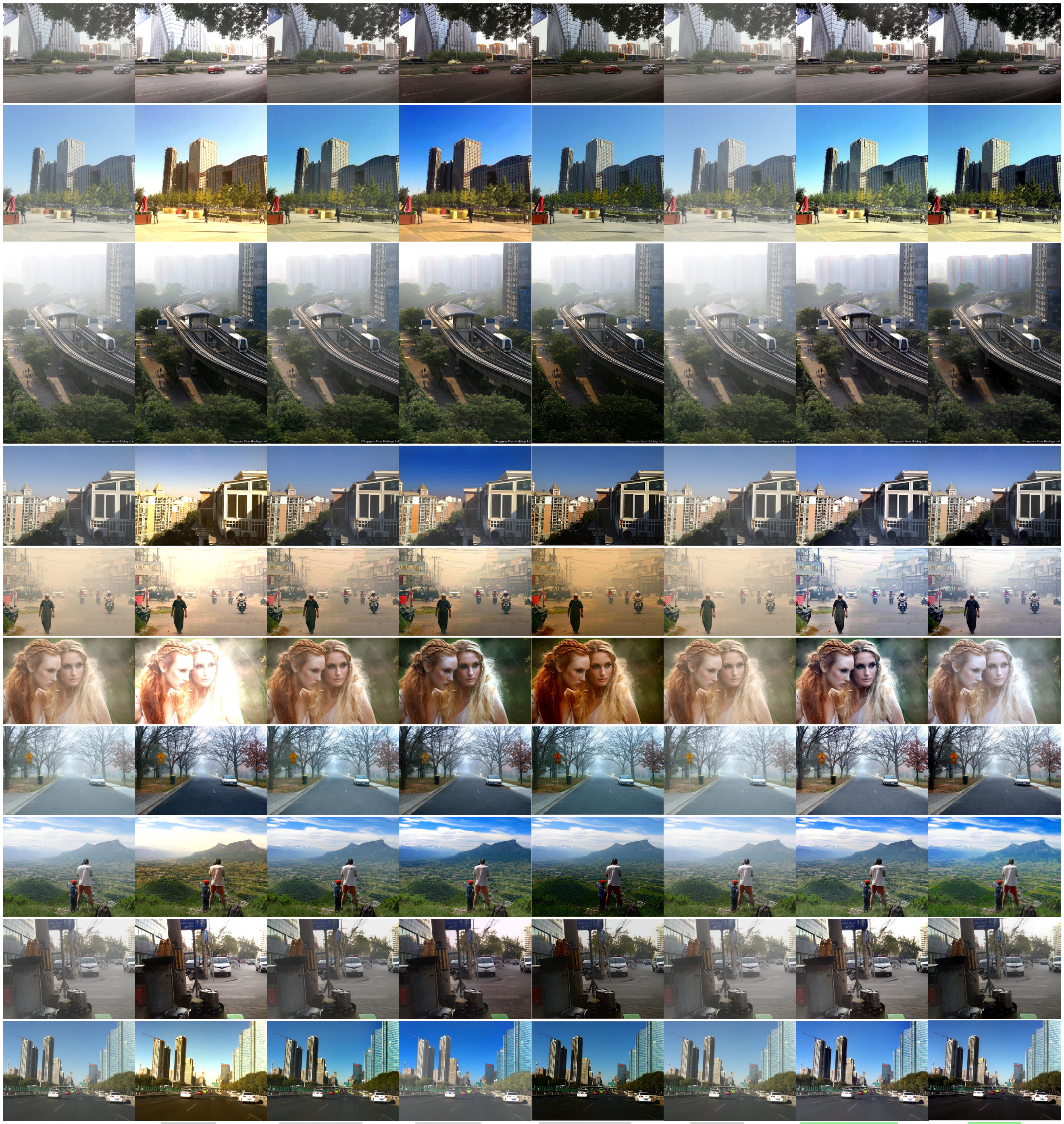
2.2. Underwater image enhancement

Input DCP [1] HRDCP [7] retinex [3] Dive+ ULAP [8] Rank One [5] Ours

Figure 2. Underwater image enhancement results obtained by different methods. (The images are best viewed in the full-screen mode.)

Underwater image enhancement faces a series of unique challenges, including color shifts and low contrast caused by the scattering and absorption of light by water. To address this, we have developed a novel image optimization technique aimed at improving the visual effect of underwater images. Our LFP method has been compared with other dehazing and sandstorm removal methods (such as DCP and HRDCP), other underwater image optimization methods (like Retinex, ULAP, Rank One), and commercial applications like Dive+. The comparison results are shown in Fig 2. Although some traditional image optimization techniques can improve image quality to some extent, they are not sufficiently effective in handling the unique challenges of underwater environments, such as severe color bias. This is likely because these methods are primarily designed based on terrestrial imaging theories, overlooking the significant differences between imaging mechanisms in underwater and terrestrial environments. LFP demonstrates superior robustness in handling the unique challenges of underwater environments, effectively restoring the natural colors and contrast of images. This is because LFP can effectively deal with the color bias of underwater environments, providing clearer and more natural image results. Therefore, our proposed method offers a more effective solution for addressing the visual quality degradation caused by underwater environments.

2.3. Haze



Input DCP [1] MSCNN [6] LDCP [10] AOD-Net [4] CAP [9] Rank One [5] Ours

Figure 3. Dehazing results obtained by different methods. (The images are best viewed in the full-screen mode.)

3. Quantitative Experiments

We conducted a simple quantitative analysis.Tab 2 below which summarizes the Peak Signal-to-Noise Ratio (PSNR) values for different methods under varying adverse weather scenarios. It is evident from the table that LFP outstrips the competing methods across all tested conditions, showcasing its superior capability in restoring degraded images.

Table 2. PSNRs under different adverse weather scenarios.

	DCP	BCCR	FVR	LFP
haze	19.13	14.02	11.61	21.05
sand	7.83	6.74	6.08	15.27
water	8.65	9.49	5.63	17.41

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3.1. OHaze

In practice, hazy images have been captured in presence of real haze, generated by professional haze machines, and O-HAZE contains 45 different outdoor scenes depicting the same visual content recorded in haze-free and hazy conditions, under the same illumination parameters.

NTIRE is a CVPR workshop that aims to provide an overview of the new trends and advances in those areas. Moreover, it offers an opportunity for academic and industrial attendees to interact and explore collaborations. Jointly with workshop NTIRE organised in 2018 the first image dehazing online challenge.

O-HAZE has been employed in the dehazing challenge of the NTIRE 2018 CVPR workshop.

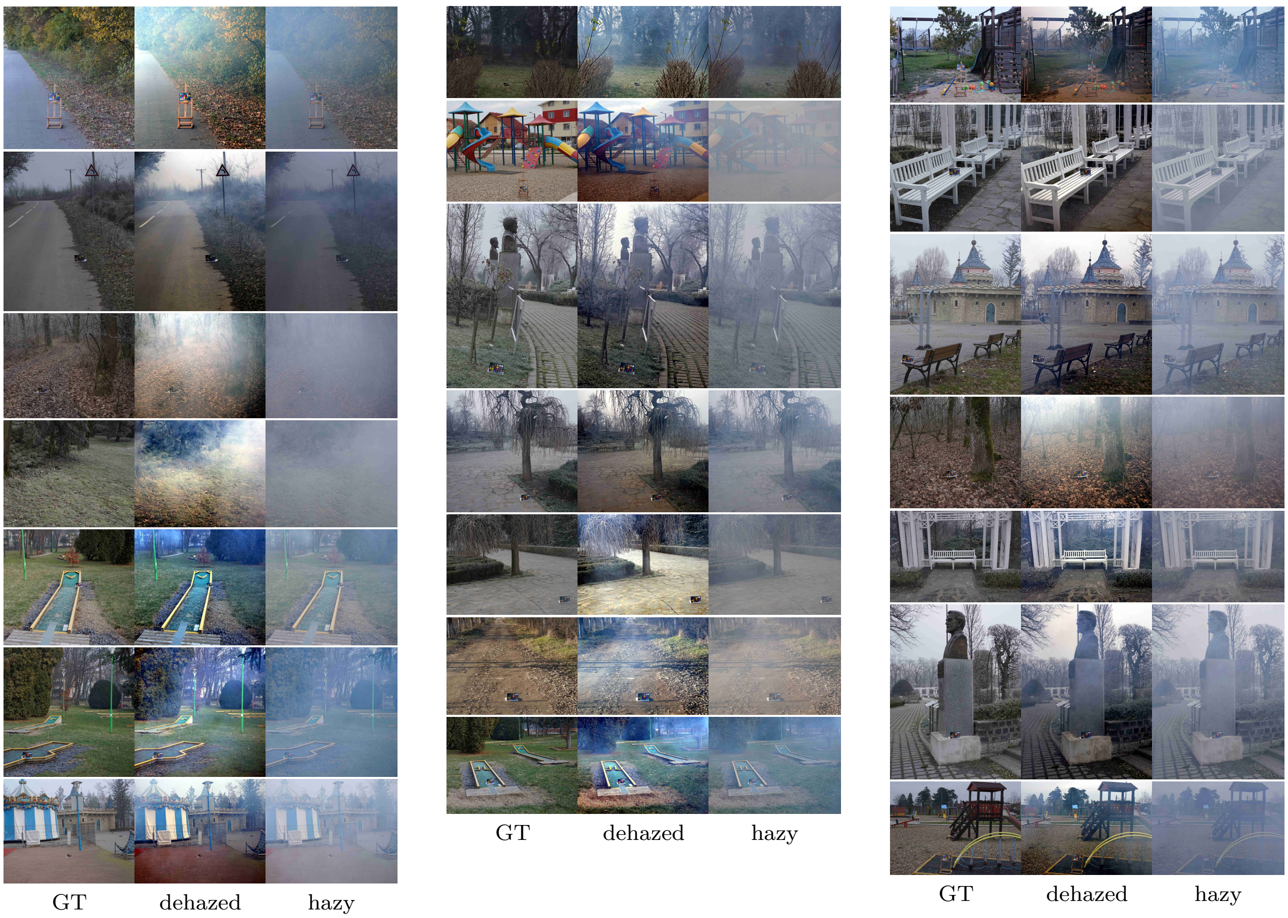

Figure 4. Dehazing results on OHaze dataset. (The images are best viewed in the full-screen mode.)

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4. Comparative Analysis

To obtain the luminous flux F and its variation rate ΔF, LFP can calculate both from RGB images and grayscale images (equal to the V channel in HSV color space). These two computation methods show no significant difference in visual effects, as is shown in Fig 5.

Hazy GT LFP_HSV LFP_RGB

Figure 5. Comparative Analysis of the Dehazing Effect using RGB and Grayscale Images, there is no significant difference between the two methods.

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