Light Pollution Reduction in Nighttime Photography

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Abstract

Nighttime photographers are often troubled by light pollution of unwanted artificial lights. Artificial lights, after scattered by aerosols in the atmosphere, can inundate the starlight and degrade the quality of nighttime images, by reducing contrast and dynamic range and causing hazes. In this paper we develop a physically-based light pollution reduction (LPR) algorithm that can substantially alleviate the aforementioned degradations of perceptual quality and restore the pristine state of night sky. The key to the success of the proposed LPR algorithm is an inverse method to estimate the spatial radiance distribution and spectral signature of ground artificial lights. Extensive experiments are carried out to evaluate the efficacy and limitations of the LPR algorithm.

1. Introduction

A side effect of urbanization is wide spread of nighttime light pollution caused by pervasive artificial lighting and increased density of aerosols in the atmosphere. As light pollution distorts the energy level and spectral signature of natural light in the night, it degrades the quality of nighttime images. For example, nowadays it is becoming increasingly difficult to capture the Milky Way with a camera; enthusiastic night sky photographers are known to go great distances just to escape the city lights. But not everyone has the means and time to travel to a location free of artificial lighting. Even a weak level of light pollution can ruin artistic appeal of night sky photos, because long exposure required to capture distant faint stars will also accumulate the small amount of artificial lighting to a noticeable level of greyish/brownish background. In addition, light pollution may be a hindrance to nighttime photography of city scenes as well. For example, a desired image composition requires shooting far away illuminated buildings or other structures at a spot where nearby street lighting cannot be escaped.

As light pollution problem cannot be physically corrected, the only solution is to algorithmically neutralize unwanted effects of light pollution on nighttime photos. This requires to model the image formation process \( \hat{I} = F(I, J) \), where \( I \) is the ideal image free of interference of artificial lighting \( J \), and \( \hat{I} \) is the image acquired in presence of \( J \), and solve the inverse problem of recovering \( I \) from \( \hat{I} \). The above stated modeling and algorithmic problem of removing light pollution in nighttime photography is the main theme and contribution of this paper. We succeed in designing the algorithm and achieving our design goal as can be previewed in Fig. 1. The ability to image nighttime beauty of pristine nature or sophisticatedly-lit man-made structures is much desired in many existing and potential applications, such as visual arts, high dynamic range imaging, environment study, and astronomy. To the best of our knowledge, we are the first to attack the problem of light pollution reduction (LPR) for nighttime photography.

Some previous publications on the subject of light pollution are about its adverse effects on the astronomical observations \([7, 23]\). Other papers discuss about the impact of light pollution on human health and environment \([3, 4, 8]\). In the field of computer graphics, Jensen et al. studied the problem of realistically rendering night sky images \([15]\). Their work is based on physically modeling nighttime illumination effects of astronomical bodies, assuming zero artificial lighting.

In the perspective of image restoration, most relevant to this work is the subject of image dehazing, which has
been extensively researched, including traditional image processing algorithms \cite{5 11}, deep learning based algorithms \cite{18 27 32}, and some algorithms especially for nighttime dehazing \cite{16 31}. The task of light pollution reduction differs from dehazing in two aspects. Firstly, the degree of light pollution is spatially nonuniform, depending on the geographical distribution and varying strength of artificial lights, and also on how the energy of artificial lighting attenuates in altitude. The mechanism of light scattering in hazy weather is simpler to model as the sun light can be considered of uniform strength in atmosphere and having a white spectrum. Secondly, the original signal strength in nighttime images is much weaker than in day time images. The low signal-to-noise ratio makes the restoration task more difficult in the former case than in the latter case.

2. Problem background

The recovery of light pollution free nighttime images is an inverse problem stated below:

\[ \hat{I} = I + J \]  \hspace{1cm} (1)

where \( \hat{I} \) is the light-polluted image captured by camera, \( I \) is the pristine nighttime image that could only be acquired in total void of artificial lights by a perfectly static camera with long exposure, and \( J \) is the jamming image formed by artificial lights reflected by aerosols towards the camera. The formation of light-polluted image \( \hat{I} \) is schematically depicted in Fig. 2. Although precise recovery of \( I \) or equivalently \( J \) from \( \hat{I} \) in terms of atmosphere science is very difficult, we aim to develop a practical method that can neutralize light pollution and approximate \( I \) in perceptual sense. To this end, we derive an approximate physical model for the light pollution effect \( J \).

The scattering of ground artificial lights by aerosols is the main cause of light pollution. The ideal modeling of light pollution is highly complex, if not impossible, as the scattering effects depend on the types, orientations, sizes, and distributions of aerosols permeating the atmosphere, as well as wavelengths, polarization states, and directions of the ground lights \cite{13 19 21 22}. We simplify the development of light pollution model by assuming homogeneous atmosphere, namely, aerosols have uniform density and they scatter lights isotropically.

Practical light scattering models seemed to follow the work of Narasimhan and Nayar \cite{21}. A light gets attenuated as it travels. Due to aerosol scattering, a fraction of light flux is removed from the incident beam, and the remaining flux arrived at the destination point is the attenuated irradiance given by Bouguer’s exponential law \cite{11}.

\[ E(d, \lambda) = E_0(\lambda) e^{-\beta_\lambda d}, \]  \hspace{1cm} (2)

where \( E_0 \) is the irradiance of the light source prior to attenuation, \( d \) is the distance from the source to destination point, \( \lambda \) is the wavelength, and \( \beta(\lambda) \) is the scattering coefficient, which accounts for the ability of a unit volume of atmosphere to scatter light of wavelength \( \lambda \) in all directions \cite{19 20}. For point light sources that radiate isotropically like the street lights with respect to atmosphere, the above attenuation model should be modified to incorporate the inverse-square law,

\[ E(d, \lambda) = \frac{E_0(\lambda)e^{-\beta_\lambda d}}{d^2}, \]  \hspace{1cm} (3)

3. Baseline method

By light pollution of nighttime images we mean the unwanted effects of ground artificial lights being scattered by aerosols in atmosphere. To remove visual effects of light pollution, we need to model and compute the light pollution image \( J \) so that the pristine image \( I = \hat{I} - J \) can be restored. To simplify the problem, we assume that for each color band \( \lambda, \lambda \in \{R, G, B\} \), the strength of artificial lighting has a uniform distribution on earth surface, with a constant irradiance \( A_\lambda \) (a restriction to be removed in the next section).

Denote by \( E_\lambda(x, y, z) \) the pollution light irradiance of color band \( \lambda \) at spatial location \( (x, y, z) \). To keep the image and world coordinates consistent, we let the \( y \) axis represent the altitude. If the pollution lighting has uniform strength and constant color everywhere on ground surface, then \( E_{\lambda y}(x, y_0, z) \) can be considered a constant for any given altitude \( y_0 \) and wavelength \( \lambda_0 \). Therefore, the irradiance function \( E_\lambda(x, y, z) \) of artificial lighting is reduced to a univariate function \( E_\lambda(y) \) that depends on altitude only, \( \lambda \in \{R, G, B\} \). Using the light attenuation model Eq. (2), we compute \( E_\lambda(y) \) in the atmosphere by integrating the influxes of ground artificial lights that reach a point of altitude \( y \), as illustrated in Fig. 3 and obtain the radiance of the light pollution at the atmosphere point

\[ E_\lambda(y) = \int_0^\infty \frac{A_\lambda e^{-\beta_\lambda \sqrt{x^2+y^2}}}{x^2+y^2} 2\pi x dx. \]  \hspace{1cm} (4)

With a change of variable \( x = \sqrt{y^2-y^2} \), Eq. (4) can be rewritten as

\[ E_\lambda(y) = 2\pi A_\lambda \int_y^\infty \frac{e^{-\beta_\lambda l}}{l} dl, \]  \hspace{1cm} (5)
\[ E_\lambda(y) = 2\pi A_\lambda \left( \ln l + \sum_{n=1}^{\infty} \frac{(-\beta_\lambda l)^n}{n \cdot n!} \right) \bigg|_{l=y} \quad (6) \]

In order to understand how the irradiance of pollution lights varies in altitude and in environment condition, we plot the \( E_\lambda(y) \) curves in Fig. 4 for different \( \beta \) values. \( \beta = 2.8 \times 10^{-5} \) corresponds to highly transparent (aerosol free) air, \( \beta = 10^{-4} \) to slightly hazy air, and \( \beta = 10^{-3} \) to haze air. The curves show that the closer to the ground (the horizon in the image), the higher the level of light pollution. Such an effect can be observed in light-polluted nighttime images, in which the lower portion of the sky is bathed in scattered ground artificial lights.

Having the energy distribution \( E_\lambda(y) \) of unwanted pollution lights in the atmosphere, now we are ready to model the image of light pollution \( J \) in Eq. 1. A pixel \( (x, y) \) in image \( J \) corresponds to a beam of pollution lights towards the camera; the pixel value is the accumulation of artificial light rays have irradiance decay according to Eq. 4. Accordingly, for better LPR results we need to improve the above baseline algorithm by making it spatially adaptive.

It is very difficult to compute the 2D radiance function \( A_\lambda(x, z) \) from input image \( I \), because \( I \) offers very little information in the \( z \) direction. The next best and feasible step is to model the horizontal variations of \( A_\lambda(x, z) \), or the marginal distribution of pollution light radiance along the horizon. Projecting \( A_\lambda(x, z) \) to the \( x \) axis and reducing it to \( A_\lambda(x) \) is acceptable, because the most common composition of nighttime photos is a horizontal landscape and thus the \( x \) axis is the principal axis of the 2D function \( A_\lambda(x, z) \).

After the above simplification, the ground artificial lights can be seen as collimated light sources. The upward pollution light rays have irradiance decay according to Eq. 7. At altitude \( y \) the artificial light radiance \( A_\lambda(x) \) is reduced to

\[ E_\lambda(x, y) = A_\lambda(x) e^{-\beta_\lambda y}. \quad (9) \]
Substituting $E_\lambda(x, y)$ in Eq.\((8)\), we obtain the pollution image,

$$J_\lambda(x, y) = A_\lambda(x) \cdot \alpha(x, y),$$

$$\alpha(x, y) = \int_0^\infty e^{-\beta_\lambda \tau} \sqrt{e^{-\beta_\lambda \tau} + \gamma} \beta_\lambda e^{-\beta_\lambda \tau} d\tau. \quad (10)$$

To compute the pollution image $J_\lambda(x, y)$ using Eq.\((10)\), we need to know the horizontal radiance profile $A_\lambda(x)$ of ground pollution lights, and separately in color bands $\lambda \in \{R, G, B\}$, i.e., know the spectral signature of the pollution lights. Now we develop a method to estimate $A_\lambda(x)$ by starting from some known priors on a pure night sky without artificial lights and working its way backward. If there was a total absence of artificial lights, then the latent image $I_\lambda(x, y)$ of the night sky would have low intensity; more importantly, a horizontal strip above ground should be almost a constant, given the altitude $y_0$ and the color band $\lambda$. Therefore, if the horizontal strip $I_\lambda(x, y_0)$ of the input image is nonuniform, then $I_\lambda(x, y_0)$ reflects the spatial radiance distribution of ground artificial lighting. This gives us a clue to estimate the required spatial distribution $A_\lambda(x)$.

It follows from Eq.\((10)\) and $J_\lambda = \hat{I}_\lambda - I$ that

$$A_\lambda(x) = \frac{\hat{I}_\lambda(x, y) - I_\lambda(x, y)}{\alpha(x, y)}, \lambda \in \{R, G, B\}. \quad (11)$$

In other words, $A_\lambda(x)$ can be derived from the input image $\hat{I}_\lambda(x, y)$ as long as if the latent image $I_\lambda(x, y)$ is known for some altitude $y = y_0$ sufficiently high above. The required priors are not difficult to be drawn from the relatively large number of night sky images free of artificial light pollution that are available from various sources, including the Internet. Samples of such pristine night sky images are presented in Fig.\((6)\).

In nature even without artificial lighting, the night sky is still illuminated by following natural compounded sources:

- The Moon that reflects the sunlight; the Sun that is set but its light is still scattered around the edge of the Earth (a.k.a., astronomical twilight);
- The planets and stars; the zodiacal light; airglow.
- The last three account for significant portions of illumination in the moonless night sky.

By sufficiently long exposures, the effects of the above weak natural light sources can be clearly imaged as we see in Fig.\((6)\). Indeed, some researchers found that via long exposure the imaged night sky in truly dark environment appears blue like in the daytime [26, 28]. We use these images to calibrate our restoration method precisely because we want to reproduce the visual appeal of long-exposure night photography in urban surroundings without the side effects of artificial light pollution.

To proceed with the above idea, we need to roughly align the sky portions of the input image $\hat{I}_\lambda(x, y)$ and a chosen light pollution-free latent image $I_\lambda(x, y)$, called calibration image. This can be accomplished by using one of many skylines detection algorithms \([6, 14, 17]\) and scaling, if needed. To make the estimation of $A_\lambda(x)$ more robust, we choose a set $Y$ of several pixel rows in the sky far above horizon. The input image and calibration image are cross examined at these pixel rows $y_j, j \in Y$, to estimate the spatial distribution of pollution radiance $A(x)$.

In order to prevent the lights of stars and Moon from interfering the estimation of $A_\lambda(x)$, we filter both 1D signals...
natural text
Figure 9: Results of the eight tested methods on a nighttime light-polluted sky image.

Figure 10: Results of the eight tested methods on another nighttime light-polluted sky image.
Figure 11: LPR-OCTM fusion results to be compared with Fig. 9(i) and Fig. 10(i).

(a) Light-polluted image  
(b) CLAHE  
(c) OCTM  
(d) LIME  
(e) Dark channel dehazing  
(f) Nighttime dehazing  
(g) DCPDN  
(h) GridDehazeNet  
(i) LPR

Figure 12: Results of the eight tested methods on another nighttime light-polluted city image.

6.1. Nighttime natural landscapes

In Fig. 1, we have seen clearly how the LPR algorithm removes light pollution in the atmosphere and restores night skies closer to the brightness and color in absence of artificial lights. Figs. 9 and 10 present the results of the eight methods in the comparison group on two more sample images of nighttime natural landscapes. The LPR algorithm is a clear winner among the eight methods in terms of restoring the night sky in a state free of artificial light pollution. LPR greatly improves the visual appeal of night sky images by reducing the background brightness above the horizon and enhancing the stars and cloud textures. The other seven methods also enhance the stars and clouds in the sky but they suffer from various color distortions and other artifacts. The enhancement methods CLAHE and OCTM adjust the sky brightness in opposite way, increasing instead of decreasing it. The LIME method turns the input night image into a daylight image. The dark channel method does dim the night sky in compensation for the scattering of artificial lights in atmosphere. But it causes severe objectionable color shifts and halo artifacts (see the windmill contour in Fig. 9(e)). The nighttime dehazing method enhances the contrast but produces severe artifacts in the sky region. The deep learning based dehazing methods DCPDN increases the overall brightness and reduces the color saturation. The GridDehazeNet generates false contours above the skyline.

[32] and GridDehazeNet[18]. This is because dehazing is a similar image restoration task, namely, removing unwanted effects of light scattering by aerosols.
In Fig. 10(c), the OCTM algorithm enhances the lake and woods below the skyline without increasing the brightness of sky too much as in the CLACH and LIME methods. Depending on personal preference, some viewers may like the OCTM effects below the skyline. This suggests a way to combine the best parts of LPR and OCTM, and merge the results of the two algorithms along the skyline into a more balanced and visually even more pleasing final output image. We present, in Fig. 11, such LPR-OCTM fusion results of the two nighttime landscape images in Figs. 9 and 10.

### 6.2. Nighttime urban scenes

Fig. 12 presents the results of the eight different methods on one nighttime downtown images of heavy light pollution. CLACH, OCTM and LIME methods fail these challenging tests badly. The dark channel method reduces the overall brightness somewhat and increases contrast modestly. But like when being used in the task of removing light pollution in nighttime natural scenes, the dehazing method generates color shifts. For the other three dehazing methods, similar conclusions can be made as in the case of nighttime natural scenes. Only the LPR algorithm passes the tests and successfully removes much of light pollution. It dims the sky, noticeably increases the overall dynamic range, and enhances surface details of the buildings.

### 6.3. Ablation study

All the above results are generated by the spatially adaptive version of the LPR algorithm. Fig. 13 lets the reader visually examine what changes will take place if the baseline version of the LPR algorithm is used. In this test image, the radiance of artificial lights is not uniformly distributed on the ground; the pollution radiance is much higher on the right side of the image than the left side. The oversimplified x-invariant pollution radiance model of Eq (4) is clearly inaccurate. Therefore, the baseline LPR algorithm cannot compensate for the spatial variations of the pollution light radiance. This causes the upper sky portion of the restored image Fig. 13(b) to have an increasing intensity ramp from left to right, i.e., still exhibiting a pattern correlated to artificial lights.

Finally, we discuss how to make tradeoffs between different perceptual goals by setting air quality parameter $\beta$ in the LPR algorithm. Fig. 14 compares the LPR results on a test image for assuming air is relatively clean and transparent ($\beta = 10^{-5}$) vs. less so ($\beta = 10^{-3}$). The larger the value of $\beta$ (the higher density of aerosols in the atmosphere), the more scattered light energy is removed from the input image by the LPR algorithm. Consequently, the residual effects of artificial lights become lesser, but some subtle details revealed by natural lights via long-exposure photography may get suppressed. Note the disappeared mountain top silhouette from (b) to (c) in 14. All experimental results reported above are generated with $\beta = 10^{-4}$.

### 7. Conclusions

We designed, implemented and experimented with a light pollution reduction algorithm for the task of alleviating adverse visual effects of unwanted artificial lights in nighttime photography. The algorithm is derived from a physical image formation model that accounts for the interactions of artificial lights, aerosols in atmosphere and the camera; it can characterize pollution light sources and to a large degree neutralize them in restored nighttime images of both nature and urban landscapes.
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