# Unveiling PM 2.5 Pollution Layer for Viewing Clear Scenes

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## Abstract

*Atmospheric pollution by PM2.5 is a serious problem now at Beijing, China and its neighboring countries. The de-hazing or de-fogging methods for degraded images have been a long-pending question at NASA Langley Research Center. Recently their basic Retinex model advanced into Visual Servo system. While the current main stream for unveiling the atmospheric pollution layer is based on scattering physics. Above all, a single image de-hazing model based on Dark Channel Prior hypothesis is most notable in practice. The keys to unveiling the pollution layer lie in the two points:* [1] *how to extract the skylight and* [2] *how to estimate the scene transmittance. This paper proposes a simple but effective de-hazing algorithm with banding-free and low computation costs referring to the Dark Channel Prior hypothesis. The simulation shows how the proposed model works to look the scene through heavy air pollution.*

## Introduction

As a NASA space development project, the de-hazing task has been a long-pending question to enhance the image visibility from cosmic space. Langley Research Center introduced the Center/Surround Retinex[1] model to their de-hazing method and finally evolved to "visual servo"system[2] by integrating the tone, sharpness and contrast mapping algorithms based on statistical scene visibility analysis. While, the current de-hazing methods based on atmospheric scattering model by McCartney[3] evolved into practical single-image models by Fattal[4], Tan[5], Tarel[6], Yu[7] and so on. Above all, the Dark Channel Prior model by He et al[8] is most attractive because of its high performance. The author improved and simplified[9] the He's algorithm to get a banding-free image with saving the computation costs.

The requirements for solving this ill-posed de-hazing problem are summarized on the following two points.

[1] Extraction of ***skylight*** **a**s a scene illumination

[2] Estimation of ***scene transmittance***

The paper aims to present a simple but effective de-hazing algorithm applicable to mobile camera for safe driving or to surveillance system for looking clear scenes through atmospheric pollution layer such as PM 2.5.

The proposed algorithm offers its advantages on the above two key points of

[1] The ***skylight*** is extracted from the ***local minimum*** in the ***luminance channel Y*** not the *RGB* channel.

[2] In the dark channel prior process to estimate the ***scene transmittance***, the conventional local minimum filter is replaced by an ***edge-preserving smoothing filter.*** This simplifies the total algorithm by omitting the most troublesome ***soft-matting*** process to reduce the banding artifacts.

[3] In addition, the ***smoothing*** parameters are automatically preset depending on the edge slope through ***gradient filter.***

## De-Hazing Algorithm

Fig.1 overviews the flow diagram of proposed de-hazing algorithm based on the atmospheric physics.

The objective of algorithm is to restore the scene *albedo* $\boldsymbol{\rho}$ or scene radiance $\boldsymbol{J}$ of haze-less scene by unveiling the pollution layer from an observed single camera image $\boldsymbol{I}$.

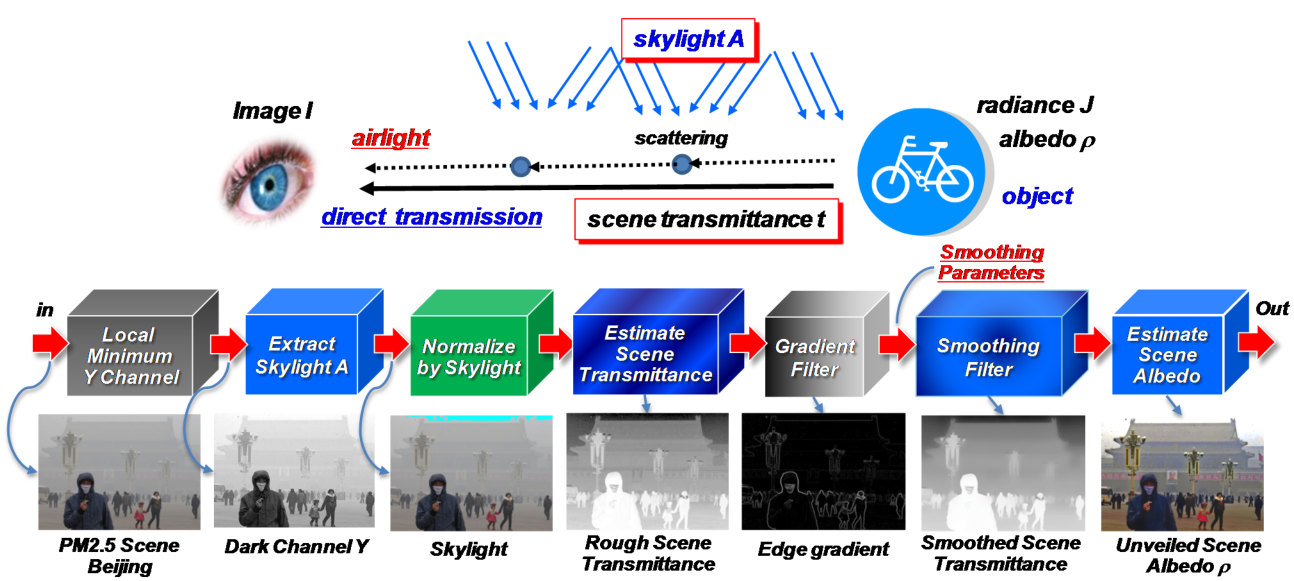


***Figure 1*** *Overview of proposed de-hazing algorithm based on atmospheric scattering physics*

## Atmospheric Scattering and Attenuation

The hazed camera image $\boldsymbol{I}(z)$ is composed of two parts as given by

$$\boldsymbol{I}(z) = \boldsymbol{J}(z)\boldsymbol{t}(z) + \boldsymbol{A}(1-\boldsymbol{t}(z))$$
$$where,\ \boldsymbol{J}(z) = \boldsymbol{A}\boldsymbol{\rho}(z),\ \boldsymbol{t}(z) = exp^{-\beta(\lambda)\boldsymbol{d}(z)} \tag{1}$$

The 1st term denotes the direct transmission image from the scenic objects and the 2nd term means the *airlight* scattered from the *skylight* $\boldsymbol{A}$. The *skylight* $\boldsymbol{A}$ acts as a scene illumination and the *airlight* causes the hazy scene by veiling the direct transmission image. $\boldsymbol{J}(z)$ and $\rho(z)$ denote the scene ***radiance*** and ***albedo*** without *airlight*.

The scene transmittance $\boldsymbol{t}(z)$ is attenuated exponentially according to the scene depth $d(z)$ with scattering coefficient $\beta(\lambda)$. Since the **Mie scattering** is dominant for floating particles with larger size than wavelength such as PM2.5 or mist, the scattering coefficient is assumed to be a constant $\beta(\lambda)\cong\beta$ independent of wavelength. Here, note that $z=(x, y)$ denotes each pixel coordinates in the 2-D camera image $\boldsymbol{I}(z)$ captured from the objects at scene depth $d(z)$.

Now the scattered flux $dF$ from the floating particles with a small volume $dV$ at distance $r$ is given by

$$dF(r,\lambda) = k\beta(\lambda)dV,\ dV = r^2 dr d\omega \tag{2}$$

Where, $k$ is a constant and $d\omega$ denotes a solid angle.

Hence, the irradiance change $dE$ by $dF$ is described as

$$dE(r,\lambda) = dF(r,\lambda)e^{-\beta(\lambda)r} / r^2 \tag{3}$$

The increase $dL$ in radiance $L$ is calculated as

$$dL(r,\lambda) = dE(r,\lambda)/d\omega = k\beta(\lambda)e^{-\beta(\lambda)r}dr \tag{4}$$

Thus the accumulated scattering between $r$=0 (camera) and $r$=$d$ (object) denotes the *airlight* radiance, that is

$$L(d,\lambda) = \int_0^d dL(r,\lambda)dr = k\left(1-e^{-\beta(\lambda)d}\right) \tag{5}$$

Since Eq. (5) denotes a monotonously increasing function, the *airlight* is more amplified as taking the longer path.

Letting the *airlight* radiance be $L_\infty$ at $d=\infty$, Eq. (5) is simply described for Mie scattering with $\beta(\lambda)\cong\beta$ as

$$L(d) = L_\infty\left(1-e^{-\beta d}\right) \tag{6}$$

In conclusion, the *airlight* radiance at infinite distance is assumed to be the skylight $\boldsymbol{A}\cong L_\infty$.

## Simplification of Dark Channel Prior Model

The proposed model tried to simplify the dark channel prior algorithm to restore the scene *albedo* $\boldsymbol{\rho}$ more easily. First the *skylight* $\boldsymbol{A}$ is extracted from the luminance channel $Y$ not $RGB$. Secondly, the scene transmittance is roughly estimated without local minimum filter.

### *Luminance-based Extraction of Skylight*

To estimate the *skylight* $\boldsymbol{A}$, He et al performed the dark channel prior operation to $\boldsymbol{I}(z)$, which selects the darkest channel from $RGB$ and replaces the pixels' values by the lowest one in a local minimum filtered area $\Omega(z)$.

$$\boldsymbol{I}^{dark}(z) = \min_{y\in\Omega(z)}\left[\min_{C\in\{R,G,B\}} I^C(\boldsymbol{y})\right] \tag{7}$$

As a result, the 1st $\boldsymbol{J}$ term in Eq. (1) approaches to zero.

$$\boldsymbol{J}^{dark}(z) = \min_{y\in\Omega(z)}\left[\min_{C\in\{R,G,B\}} J^C(\boldsymbol{y})\right] \rightarrow 0 \tag{8}$$

This dark channel prior hypothesis is supported by the many observation data for hazed scenes.

Thus only the 2nd term is remained as

$$\boldsymbol{I}^{dark}(z) \cong \min_{y\in\Omega(z)}\left[\min_{C\in\{R,G,B\}} A^C\left(1-\boldsymbol{t}(\boldsymbol{y})\right)\right] \tag{9}$$

Since the *skylight* $\boldsymbol{A}$ equals the *airlight* $\boldsymbol{A}\cong L_\infty$ coming from $d=\infty$, there the transmittance must be $\boldsymbol{t}(z)\cong 0$. Thus He et al obtained the *skylight* $\boldsymbol{A}$ by finding the brightest area from the dark channel $\boldsymbol{I}^{dark}(z)$.

Different from the above method, the proposed model applied the dark channel process only to the luminance channel $Y(z)$ to simplify the procedure. Applying a local minimum filter to the luminance $Y(z)$ without taking the dark channel of $RGB$, we get

$$Y^{dark}(z) = \left\{\min_{y\in\Omega(z)}\left(Y(\boldsymbol{y})\right)\right\} \tag{10}$$

Thinking the local minimum in the dark channel must be reflected to the local minimum of the luminance channel, the *skylight* $\boldsymbol{A}$ may be estimated by extracting the brighter area $\Omega_{Sky}$ and taking the average as

$$\tilde{\boldsymbol{A}} = \underset{y\in\Omega_{Sky}(z)}{mean}\{\boldsymbol{I}(\boldsymbol{y})\}\ for\ \Omega_{Sky}(z) = area\left\{Y^{dark}(z) \geq Y_H\right\} \tag{11}$$

This simplified method proved to have the comparable performance to that by He et al as shown in Fig.2. Though the proposed method has a tendency to detect a little bit larger area as a skylight than that by He et al, its positions and colors are much the same.

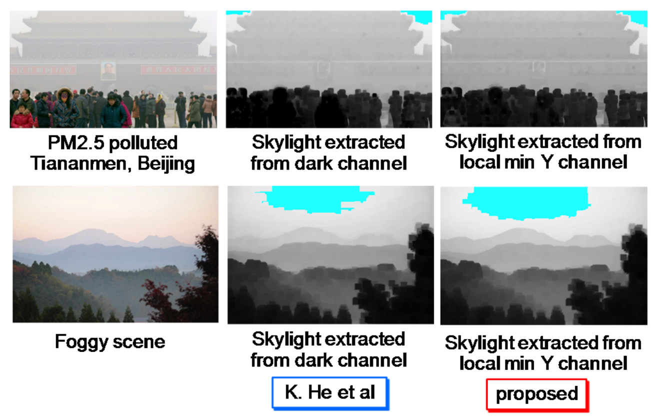


***Figure 2*** *Skylight detection in comparison with K. He et al*

### *Rough Estimation of Scene Transmittance*

Normalizing Eq. (1) by the estimated *skylight* $\tilde{A}$, it's eliminated from the 2nd term as

$$\frac{\boldsymbol{I}^C(z)}{\tilde{\boldsymbol{A}}^C} = \frac{\boldsymbol{J}^C(z)}{\tilde{\boldsymbol{A}}^C}\boldsymbol{t}(z) + (1-\boldsymbol{t}(z))\ \ for\ C = R,G,B \tag{12}$$

He et al applied the dark channel prior process to the normalized camera image in Eq. (12) again as

$$\left[\frac{\boldsymbol{I}^C(\boldsymbol{y})}{\tilde{\boldsymbol{A}}^C}\right]^{dark} = \min_{y\in\Omega(z)}\left[\min_{C\in\{R,G,B\}}\frac{\boldsymbol{J}^C(\boldsymbol{y})}{\tilde{\boldsymbol{A}}^C}\right]\boldsymbol{t}(z) + (1-\boldsymbol{t}(z)) \tag{13}$$

In the same way as Eq. (8) and (9), the 1st term goes to zero and the 2nd term is remained. Hence they got a rough estimation for the scene transmittance as

$$\tilde{t}(z)^{rough}(He) \cong 1 - \min_{y\in\Omega(z)}\left[\min_{C\in\{R,G,B\}} \frac{I^C(y)}{A^C}\right] \tag{14}$$

Since Eq. (14) includes the blocking boundaries caused by the local minimum filter, it leads to a fatal banding artifact hereafter.
So, the proposed algorithm omitted the local minimum filter in Eq. (14) to avoid the blocking boundaries. A scene transmittance is simply estimated as

$$\tilde{t}(z)^{rough}(proposed) \cong 1 - \left\{\min_{C\in\{R,G,B\}} \frac{I^C(y)}{A^C}\right\} \tag{15}$$

## Banding Problem in Recovering Scene Albedo

Once the skylight $A$ and scene transmittance $t(z)$ are estimated, the scene *albedo* is recovered from Eq. (1) as

$$\tilde{\rho}(z) \cong \tilde{J}(z)/\tilde{A} = \left(I(z)/\tilde{A} - 1 + \tilde{t}(z)\right)/\,Max\left[\tilde{t}(z), t_0\right] \tag{16}$$

Where, *Max* [ , ] is a limiter taking $\tilde{t}(z) \geq t_0$ for very small values of transmittance for the *albedo* $\tilde{\rho}(z)$ not to diverge.

Now, Fig.3 shows the scene *albedo* $\tilde{\rho}(z)$ unveiled with
[1] $\tilde{t}(z)^{rough}(He\,et\,al)$ and [2] $\tilde{t}(z)^{rough}(proposed)$ .

Comparing the both unveiled scenes, a heavy banding artifact appears in (f) by He et al caused by the blocking boundaries in (d) inherent to the dark channel prior process. While, the banding artifact disappears in (g) by the proposed model. However, looking both scenes carefully, the back signboard or front people in (f) look clear than (g) except the banding artifact. Although (g) is restored without banding, the image sharpness is lost instead. That is, the estimated rough scene transmittances by He et al and by the proposed model, both have their own drawbacks.
Since the scene transmittance $t(z)$ denotes a depth map from camera to each object, it should be flat for the objects located at the same distance. Now, the estimated $\tilde{t}(z)^{rough}(proposed)$ looks to be inferior to $\tilde{t}(z)^{rough}(He\,et\,al)$ in flatness as shown in Fig.3 (e).
This irregularity is the drawback in the proposed method and the reason why the sharpness is lost in Fig. 3 (g).

## Refining Scene Transmittance

The proposed model applied the *smoothing filter* to the rough scene transmittance for flattening the irregularity as

$$\tilde{t}(z)^{smooth} = SmoothingFilter\left[\tilde{t}(z)^{rough}\right] \tag{18}$$

Since the popular *Gaussian filter* leads to banding artifact caused by the *isotropic* diffusion with edge blurring, it's required to use an *edge-preserving smoothing filter*.

The following two types of *edge-preserving smoothing filters* are examined: [A] ***Perona-Malik*** *filter* [B] ***Bilateral*** *filter*

## Smoothing with Perona-Malik (PM) Filter[10)]

*Perona-Malik filter* is based on *anisotropic thermal diffusion*. The scale-space diffusion when applied to the scene transmittance $t(z, \tau)$ is described by

$$\partial t(z,\tau)/\partial\tau = div[c(z,\tau)\nabla t(z,\tau)] = c(z,\tau)\Delta t(z,\tau) + \nabla c(z,\tau)\nabla t(z,\tau) \tag{19}$$

Where, the operators denote ***div*** =*Divergence*, $\nabla = (\partial/\partial x, \partial/\partial y)$ =*Gradient*, and $\Delta = (\partial^2/\partial x^2, \partial^2/\partial y^2)$=*Laplacian*.

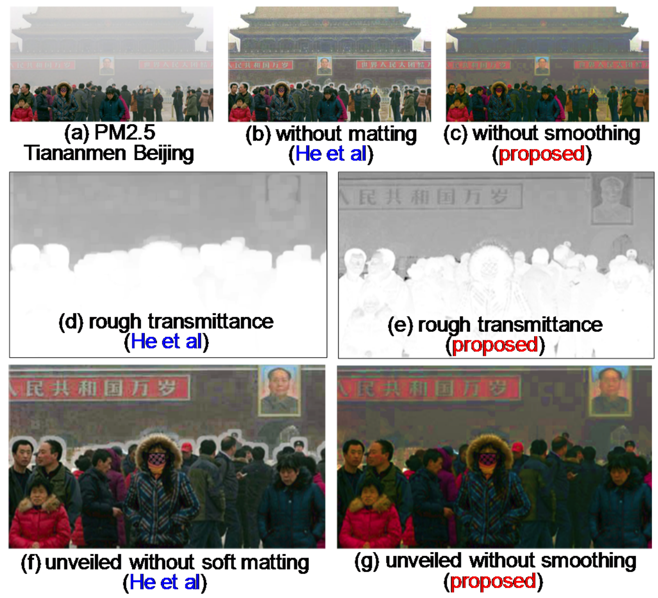


***Figure 3*** *Problems in rough estimation of scene transmittance*

In Eq. (19), $c(z, \tau)$ denotes a thermal diffusion coefficient and $\tau$ means passage of time as a scale parameter.
In case of $c(z, \tau)$=constant, Eq. (19) means *isotropic* diffusion just working as usual *Gaussian filter*.

Here, *anisotropic* diffusion is assumed for $c(z, \tau)$ changing with *Gaussian Gradient* of $t(z, \tau)$ like as

$$c(z,\tau) = G_D(\|\nabla t(z,\tau)\|, \tau) \tag{20}$$

$G_D(\bullet, \sigma)$ denotes a *Gaussian* with standard deviation $\sigma$. The diffusion across the edges is suppressed and a ***PM*** *filtered* scene transmittance $\tilde{t}(z,\tau,k,\sigma)^{PM}$ is got by solving Eq. (19), where the degree of diffusion changes with time $\tau_n = n\Delta\tau$ converging to a maximum at $\tau \to \infty$ for large $n$ and $k$ denotes diffusion strength.

## Smoothing with Bilateral (BL) Filter[11)]

*Bilateral Filter* is composed of a couple of two *Gaussian* filters, one used for spatial smoothing and another for edge preserving as given by

$$\tilde{t}(q,\sigma_S,\sigma_R)^{BL} = W^{-1}\sum_{p\subset\Omega(q)} G_S(\|p-q\|)\,G_R\big(\tilde{t}(p)-\tilde{t}(q)\big) \tag{21}$$

$G_S(\bullet, \sigma_S)$ works as a spatial filter to smooth $\tilde{t}(z)$ for the neighborhood pixels in $p\subset\Omega(q)$ with a standard deviation $\sigma_S$. While, $G_R(\bullet, \sigma_R)$ works to suppress the smoothing for the pixels with high intensity difference in the edge area with $\sigma_R$ smaller than $\sigma_S$.

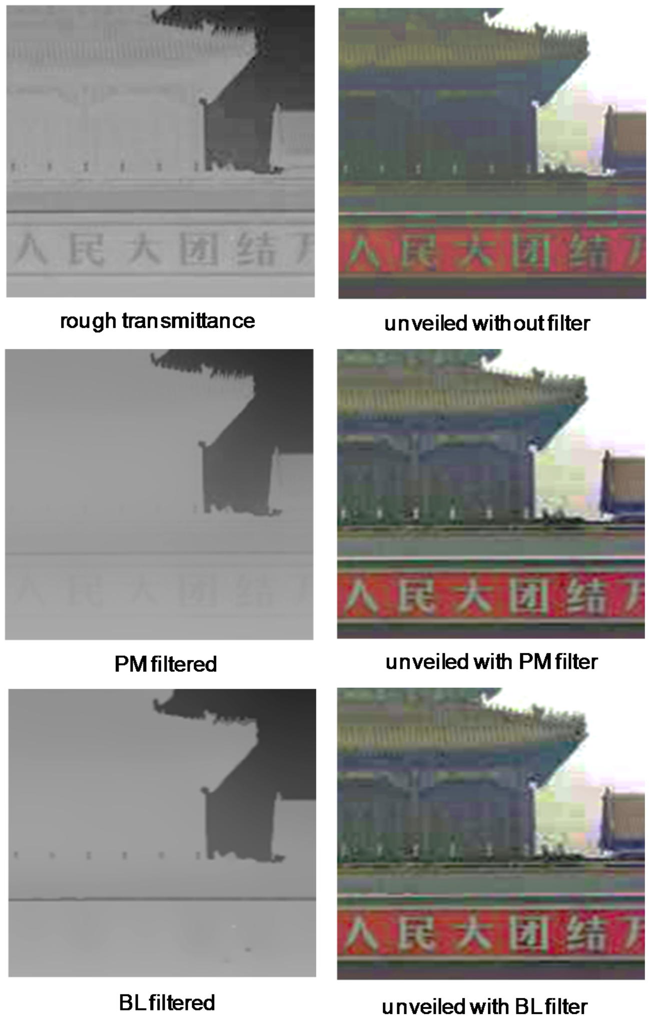


***Figure 4*** *Visibility improvement by smoothing rough scene transmittance*

## Scene-Adaptive Smoothing

The smoothing parameters ($\tau$, $k$, $\sigma$) for ***PM*** ($\tau$, $k$, $\sigma$) and ($\sigma_S$, $\sigma_R$) for ***BL*** ($\sigma_S$, $\sigma_R$) filters are desirable to be set automatically. The proposed model tried to set them scene-adaptive. Here the standard deviation $\sigma_m$ for $\tilde{\boldsymbol{t}}(\boldsymbol{z})$ is used as a measure as

$$\sigma_m{}^2 = Variance\left\{\nabla\, \tilde{t}(z)^{rough}(proposed)\right\} \tag{22}$$

Typically, ***PM*** filter worked stable around (scale $\tau \approx 50\%$, diffusion strength $k \approx \sigma_m/2$, gradient $\sigma \approx 5\sigma_m$) and ***BL*** filter around ($\sigma_S \approx \Omega$, $\sigma_R \approx 3\sigma_m$).

## Experimental Results

Fig.4 shows a close-up in the improved result without and with ***M*** and ***BL*** filters applied to Fig.3. The smoothing parameters for both filters are automatically set referring to the *gradient* of $\tilde{t}(z)^{rough}$ .The unveiled scene visibilities in detail are clearly much improved by the smoothing. The whole *Tiananmen* scene restored by unveiling this heavy PM2.5 pollution is shown in Fig.5. It's shown that the scene transmittance reflects the distance from darker for far and lighter for near corresponding to the perspective.


***Figure 5*** *Unveiled Tiananmen by proposed method for heavy PM2.5 pollution*

The characters in the back wall signboard are readable and the clear Tiananmen building can be looked through the pollution layer. Fig. 6 shows another scene taken in front of Mao Zedong panel at Tiananmen. It shows how the proposed scene transmittance refined with gradient-based BL filter instead of soft matting by K. He et al, works well to look the clear panel through PM 2.5. Fig.7 is a different sample applied to a heavy fogged scene taken by NASA. Though it seems very hard to unveil, a clear scene is restored through the dense fogs with the aid of PM filter. Fig.8, Fig. 9, and Fig.10 compare the proposed model with typical existing methods. Fig.8 shows the estimated scene albedo $\rho$ for usual foggy scenes. The proposed model worked much the same as the most recognized model by He et al. Fig. 9 also compares the estimated scene albedo with typical models, where the skylight is hard to extract for the misty lake scene (b), because the sunlight doesn't exist in the scene. Lastly, the estimation of scene radiance $\boldsymbol{J}$ is compared in Fig.10. In all those samples, the proposed model worked almost equally or better.

## Conclusions

The paper proposed a simplified de-hazing model based on atmospheric physics. The model worked much the same as K. He et al without soft matting but with an edge-preserving smoothing filter. In spite of very simplified algorithm, the proposed model is in no way inferior to other established models as a whole.

The performances of ***PM*** or ***BL*** filters were much the same. The smoothing parameters are set automatically adaptive to the scene transmittance, but not optimized yet. Further research for robust unveiling algorithm against the heavy air pollutions should be continued and the correct extraction of *skylight* for the scenes without sunlight is left behind as a future work.

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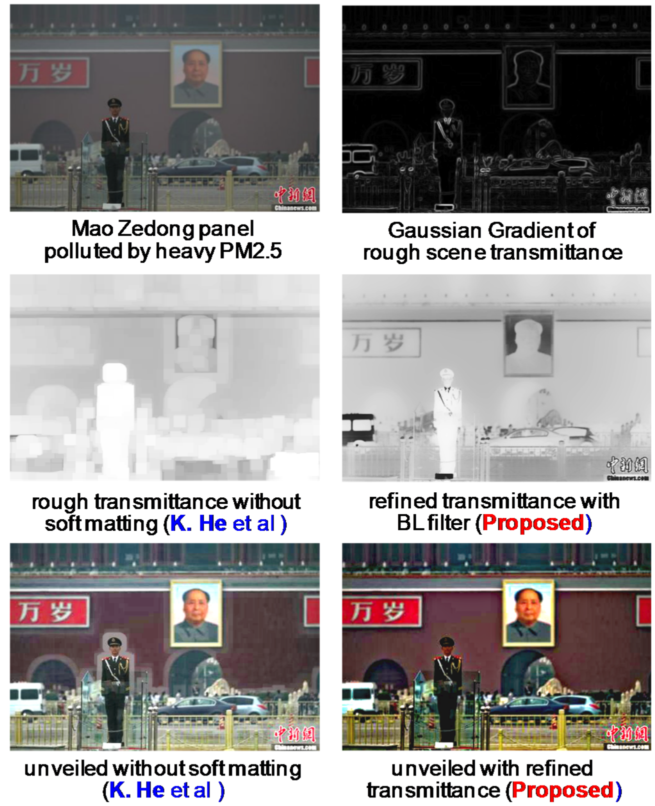


***Figure 6*** *Unveiled Mao Zedong panel by Gaussian gradient-based BL filter*

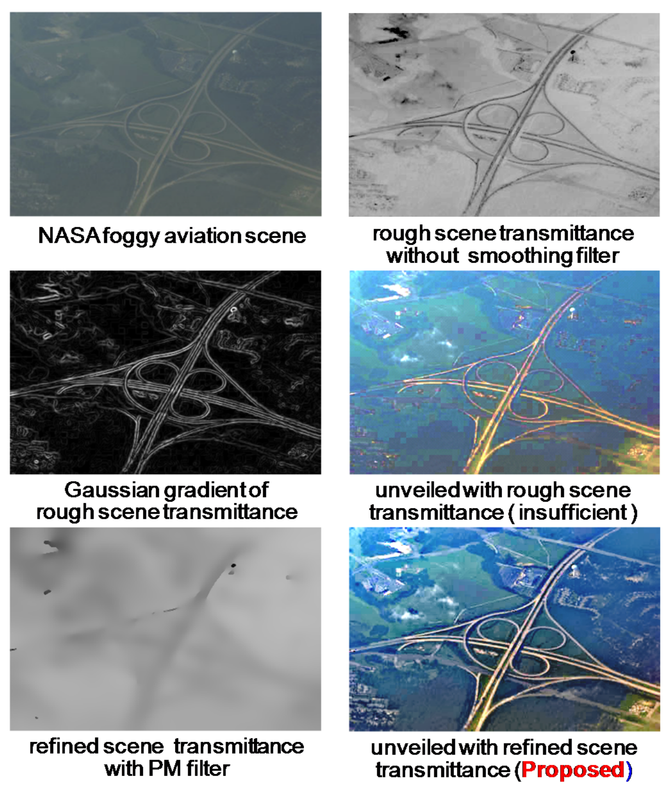


***Figure 7*** *Unveiled sample for NASA heavy fogged scenes*

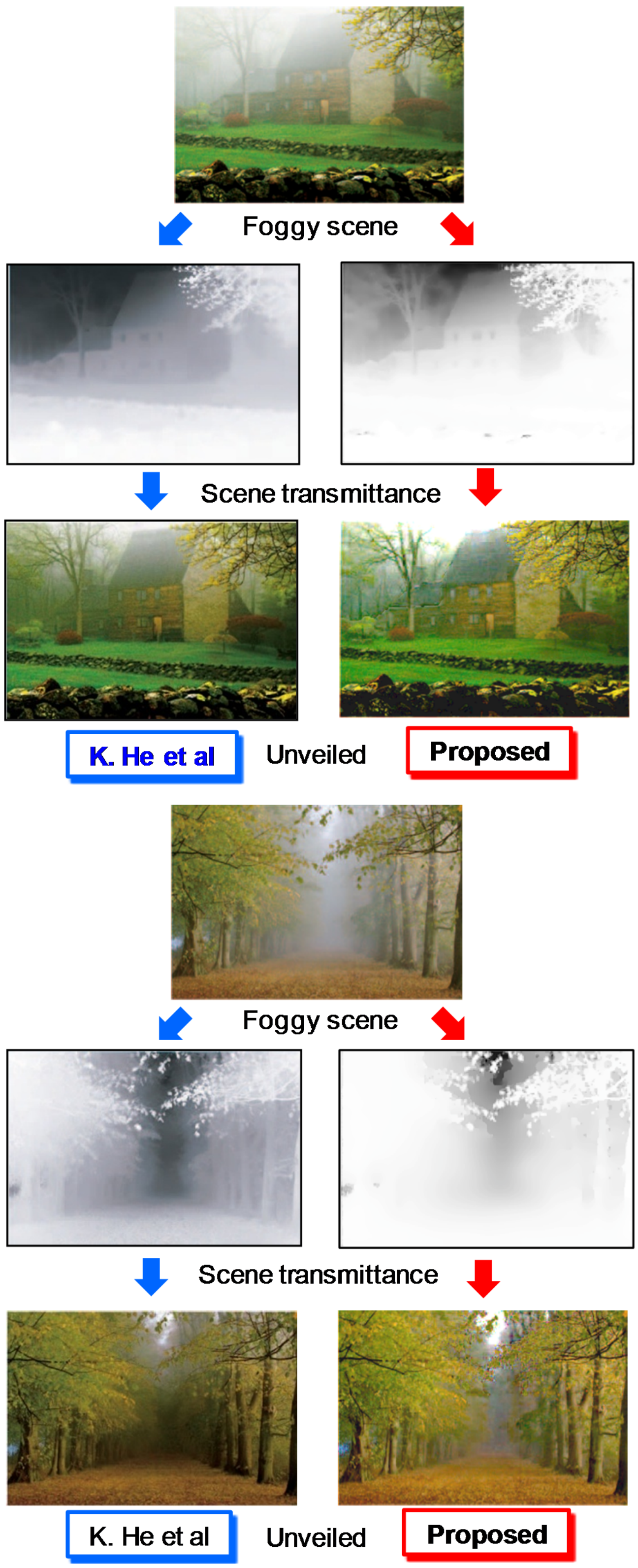


***Figure 8*** *Usual foggy scenes in comparison with K. He et al*

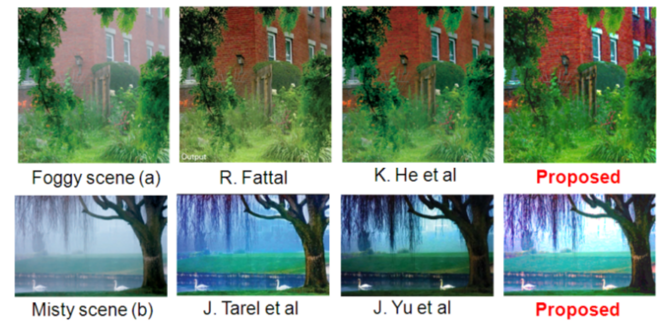


***Figure 9*** *Comparison with other typical models for scene albedo estimation*

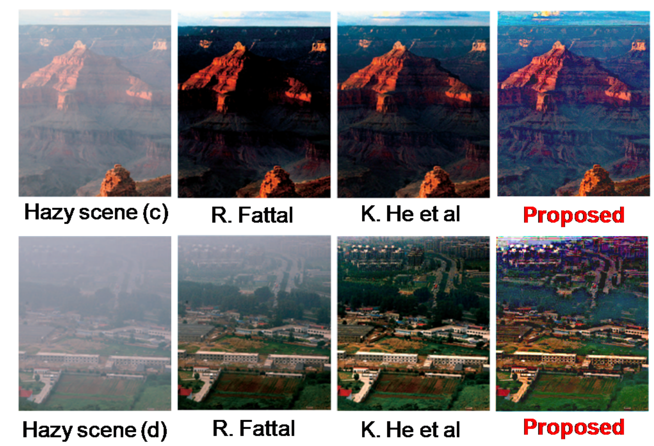


***Figure 10*** *Comparison with other typical models for scene radiance estimation*

## Author Biography

***Hiroaki Kotera*** *joined Panasonic in 1963. He received PhD from Univ. of Tokyo. After worked at Matsushita Res. Inst. Tokyo during 1973-1996, he was a professor at Dept. Information and Image Sciences, Chiba University. He retired in 2006 and is working as TLO associate at Chiba University. He received 1993 IS&T honorable mention, 1995 SID Gutenberg prize, 2005 IEEE Chester Sall award, 2007 IS&T Raymond. C. Bowman award, 2009 SPSTJ and 2012 IIEEJ best paper awards. He is a Fellow of IS&T.*