EFFECTIVE LOCAL AIRLIGHT ESTIMATION FOR IMAGE DEHAZING

Codruta O. Ancuti [*], *Cosmin Ancuti*[*] *and Christophe De Vleeschouwer*[†]

[*] MEO, Universitatea Politehnica Timisoara, Romania
[†] ICTEAM, Universite Catholique de Louvain, Belgium

ABSTRACT

This paper introduces an effective strategy to enhance the visibility of hazy images, especially those obtained in night-time conditions. Compared to day-time, in night-time scenes, the lighting generally arises from multiple artificial sources and therefore may be considered intrinsically as being non-uniform. As a result, conventional global atmospheric light (airlight) estimation strategies become irrelevant. In this work, we propose a simple yet effective patch-based atmospheric light estimation. To circumvent the problem of selecting an appropriate patch size, we propose to estimate the atmospheric light on several patch sizes, and to define the local airlight as the average of those estimates. An extensive experimental validation demonstrates that the proposed strategy is able to recover the scene radiance without unwanted color-shifting, and proves that our approach is competitive compared to recent techniques in terms of restored image quality.

***Index Terms*—** night-time dehazing, local airlight estimation, hazy

I. 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 [1], or multiple images [2]. More recently, single image-based dehazing techniques have been proposed [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16]. They generally consider the inversion of the simplified Koschmieder's optical model [17], and build on different priors to estimate its two unknowns, namely the transmission map and the airlight, assumed to be constant. Tan [4] 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 [3] 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. [5] 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. [18] introduced a regularization method to refine the transmission estimated based on the dark channel prior, while Zhu et al. [19] assume that the depth can be estimated from pixel saturation and intensity.

These dehazing techniques, by assuming constant airlight, are essentially targeted towards day-time hazy scenes. As can be observed in figure 1, those approaches suffer from important limitations for night-time hazy scenes. Night-time hazy scenes commonly involve artificial light sources, which tend to introduce additionally glowing artifacts. To address this issue, several dedicated night-time dehazing methods [22], [23], [21], [24], [25], [26] have been introduced recently. Pei and Lee [22] adopt a color transfer strategy in addition to dark channel prior to estimate haze thickness and airlight [5], [27]. In Zhang et al. [23], the non-uniform incident illumination is first estimated for color correction purpose. Li et al.[21] propose to extend the optical model to incorporate the atmospheric point spread function for modeling the glowing effect.

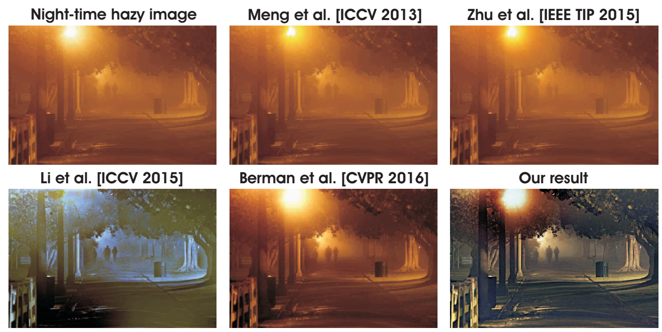

Fig. 1. *Night-time hazy images are challenging and recent single-image dehazing techniques [18], [19] suffer from important limitations when applied to such images. In some extreme conditions, recovering the color-appearance is also challenging for solutions that estimates the airlight locally [20] or dedicated night-time dehazing algorithms [21]*

In this paper, we introduce a simple but effective approach to estimate locally the atmospheric light. While the popular dark-channel strategy [27] computes a constant atmospheric light over the entire image, our strategy is able to deal with non-uniform illumination generated by the multiple light-sources present in night-time scenes. Inspired by our previous work [24], we estimate the atmospheric light locally by computing it on a grid of patches. To circumvent the tricky question of selecting an appropriate patch size, we compute two different estimates of the local atmospheric light, respectively associated to a large and a small patch size. The use of a large patch helps in improving the global contrast, by accounting for a large scene neighborhood. A smaller patch prevents accounting from too many light sources when estimating the atmospheric light in a given location. Our optimal atmospheric intensity is simply estimated as the mean over those two patch sizes. Finally, the dehazed images are yielded using a rough transmission map estimated based on the dark channel prior [5] and inverting the optical model. A comprehensive qualitative and quantitative evaluation is provided, both for day-time and night-time hazy scenes. It demonstrates the efficacy of our approach both in terms of computational efficiency and quality of the outputs.

II. HAZE REMOVAL WITH LOCAL ATMOSPHERIC LIGHT ESTIMATION

This section presents briefly the optical model and the main physical parameters that need to be estimated to restore hazy images in the presence of non-uniform (artificial) lightning. Next, we review how the dark-channel prior is used to estimate the transmission map, and finally we introduce our proposed local estimation of the airlight.

II-A. Optical Model of Hazy Scenes

Haze is an atmospheric phenomena characterized by small droplets nuclei. As a consequence, in hazy conditions, the light that is passing through the medium is scattered, deviated and attenuated. The image formation process is expressed mathematically by the the Koschmieder's model [17]. Based on this model, the recorded light intensity $\mathcal{I}$ of each pixel coordinate x is composed from two main additive components - the *direct attenuation* $\mathcal{D}(x)$ and the *airlight* $\mathcal{A}(x)$:

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

The *direct attenuation* corresponds to the fraction of the reflected light that reaches the observer due to the absorbing and scattering. The *airlight* term is the principal source of the color shifting. In this equation, $\mathcal{J}(x)$ represents the scene radiance of a clear medium (haze-free image), $T(x)$ is the *transmission* along the cone of vision, and A_∞ is the atmospheric intensity (airlight). The transmission map $T(x)$ is directly related to the depth of the scene. For homogeneous medium, it is mathematically defined as $T(x) = e^{(-\beta\ d(x))}$, where β represents the medium attenuation coefficient (due to the scattering), and $d(x)$ is the physical distance from the camera to the considered surface.

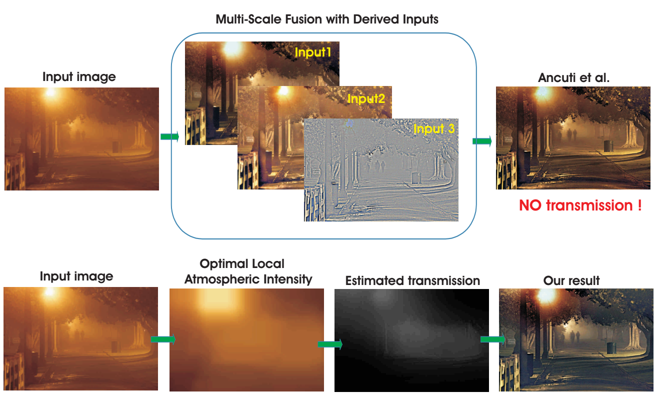

Fig. 2. Overview. *Compared with [24](shown in the top row), our solution (shown in the bottom row) is more robust and straightforward to be implemented. First, since we do not employ multi-scale fusion using a Laplacian pyramid decomposition, the computation complexity is significantly reduced. Another advantage of our approach is that we solve only once the optical model Eq. 1 (in [24] this is required for every derived input). Finally, our optimal atmospheric intensity estimate allows to compute a transmission map using Eq.2.*

II-B. Transmission estimation based on dark channel prior

To estimate the transmission map, we adopt the well-known dark channel prior introduced by He et al. [27]. For day-time scenes, the dark channel prior assumes that, in non-sky regions, the radiance $J(x)$ has a small value for at least one color channel, in at least one pixel of each patch. Based on the Koschmieder' optical model [17] it has been observed that the transmission map is correlated with dark channel estimate $I_{DC}(x) = \min_{y\in\Omega(x)}(\min_{c\in r,g,b}(\mathcal{I}^c(y)/A_\infty{}^c))$. As a consequence, the transmission map $T(x)$ can be estimated from the Koschmieder's model, by computing:

$$T(x) = 1 - \min_{y\in\Omega(x)}\left(\min_{c\in r,g,b}\mathcal{I}^c/A_\infty{}^c\right) \quad (2)$$

where $\mathcal{I}^c$ denotes one of the color channels of the hazy image $\mathcal{I}$ while A_∞ is the atmospheric light/airlight constant ($A_\infty = [A^r_\infty, A^g_\infty,\ A^b_\infty]$), and $\Omega(x)$ represents a local patch centered on the pixel x location.

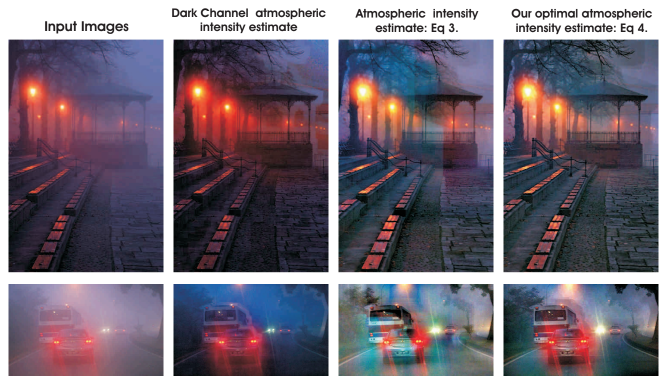

Fig. 3. Rough dehazing of night-time scenes. *Designed originally for day-time dehazing, the well-known dark channel [27] shows important limitations for such scenes because it estimates uniformly (on the entire image) the atmospheric intensity. Estimating the atmospheric intensity using a large patch in Eq.3 improves the visibility. However, employing our optimal atmospheric intensity (Eq.4), the color and details that are close to the light sources are better recovered.*

II-C. Local Atmospheric Intensity Estimation

A critical assumption that hinders the recovery of natural colors in night-time hazy images is the one that considers the atmospheric intensity (airlight) A_∞ to be constant. Early dehazing methods assumed that the atmospheric intensity can be estimated by the color vector of the pixel with highest intensity [4]. This approach was motivated by the white appearance of haze in day-time scenes. However, this estimate may fail when the scene contains white objects (which are wrongly identified as hazy pixels). To avoid such miss-identification, the transmission information has been considered in [27] to restrict the selection of haze-opaque pixels to distant pixels. In practice, these regions are mathematically defined as having the brightest dark channel, i.e. as the ones that maximize $I_{DC}(x) = \min_{y\in\Omega(x)}(\min_{c\in r,g,b}\mathcal{I}^c(y))$, where r, g, b symbolize the R,G,B color channels. This strategy is quite effective for day-time scenes, but reveals important limitations in night-time ones (see Fig. 3). In general, night-time scenes are characterized by multiple artificial and spatially non-uniform illumination sources, so that searching for a global and constant atmospheric intensity becomes inappropriate. Moreover, the fact that night-time scenes are generally subject to colored lighting makes the search for a 'white' airlight especially irrelevant.

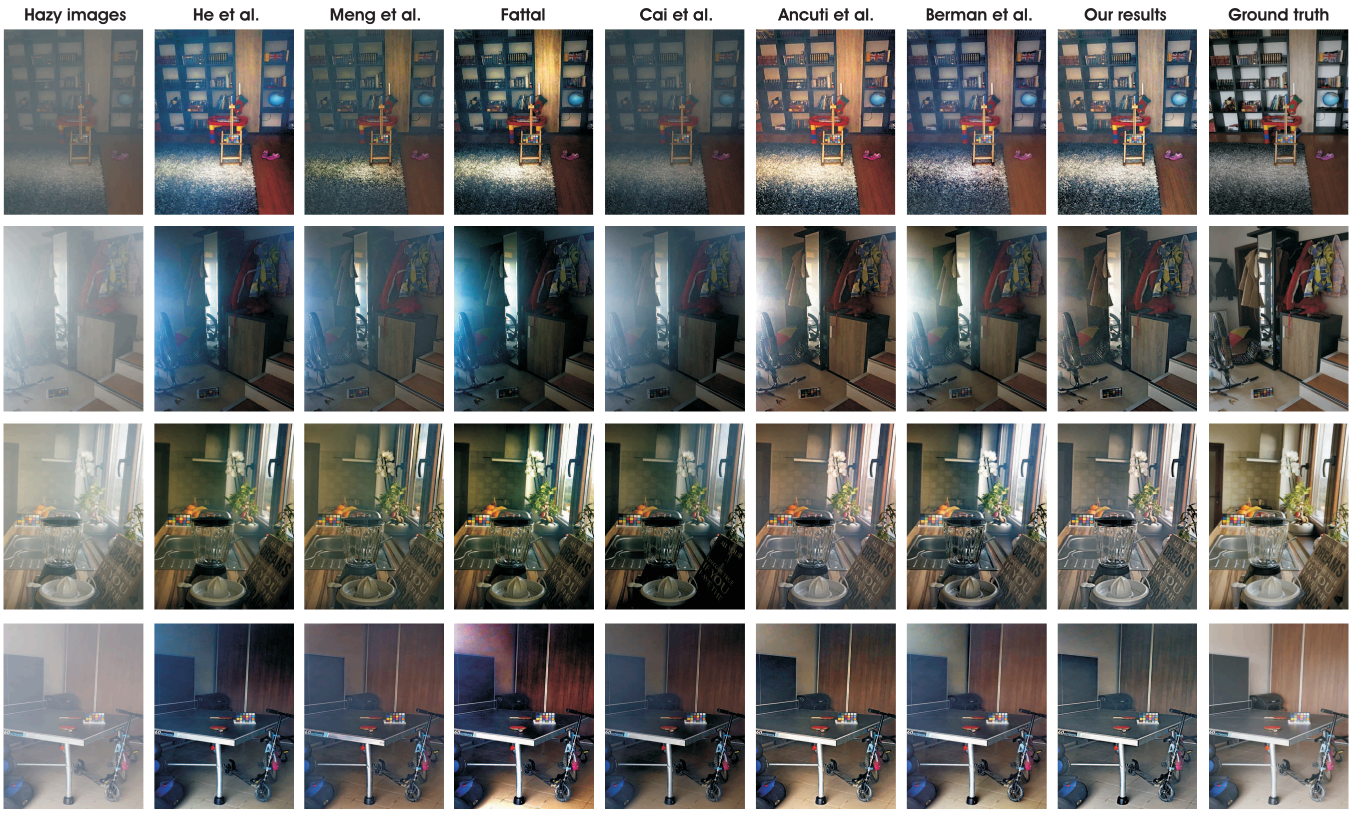

Fig. 4. ***Comparative results.*** *The first row shows the hazy images and the last row shows the ground truth. The other rows from left to right show the results of He et al. [5], Meng et al. [18], Fattal [11], Cai et al. [15], Ancuti et al. [24], Berman et al. [20] and our results.*

To address this problem, we build on our recent work [24] and estimate the atmospheric intensity $A^c_{\Omega\infty}(x)$ as a function of x. Mathematically, the local atmospheric intensity $A^c_{\Omega\infty}(x)$ is defined as:

$$A^c_{\Omega\infty}(x) = \max_{y\in\Psi(x)}\left[\min_{z\in\Omega(y)}(\mathcal{I}^c(z))\right] = \max_{y\in\Psi(x)}\left[I^c_{MIN}(z)\right] \quad (3)$$

where $\Psi(x)$ is a spatial neighborhood around the pixel coordinate x. In practice, the patch Ψ is chosen to be twice as big than the patch Ω. In addition, when the parameter $\Psi(x)$ is chosen to cover the entire image, this method behaves as a global estimator.

Selecting an appropriate size for Ω is however not straightforward. A large neighborhood willl be influenced by multiple light sources, making the estimation and compensation of the airlight inaccurate, which results in similar color shiftings than the ones encountered with global airlight estimation. In contrast, a too small neighborhood prevents effective exploitation of the dark channel prior, which fundamentally relies on a the observation of a representative distribution of pixel intensities to estimate the transmission and remove the corresponding haze. To circumvent this problem, we propose to compute two different estimates of the local $A_\infty(x)$ from Eq.3. The first one is computed with a relatively large patch size (e.g. 15% of the image size). It primarily aims at improving the image contrast by reducing the haze, with a risk of color shifting. The second one is computed using a smaller patch size (e.g. 5% of the image size). It aims at preventing wrong estimation of the $A_\infty(x)$, but might underestimate the attenuation due to haze.

Next to compute our optimal local atmospheric intensity estimate we simply calculate the mean over all the local atmospheric values using different size patches of Ω:

$$A^c_{L_{optim}\infty}(x) = (\sum_i A^c_{\Omega_i\infty}(x))/N_\Omega \quad (4)$$

where $A^c_{\Omega_i\infty}$ counts for different local atmospheric intensity estimates, and N_Ω is the number of the estimates. We observed experimentally that only two estimates, described previously, are generally sufficient in practice. One might however consider more granularity in patch sizes, especially in scenarios with multiple heterogeneous light sources.

Compared with [24], our solution is more robust and straightforward to implement. Because we do not employ multi-scale fusion using a Laplacian pyramid decomposition, the computation complexity is significantly reduced. Another advantage of our approach is that it solves the optical model only once (thereby providing the transmission as a side product), while this model needs to be solved for every input in [24] (leaving the transmission ambiguous). Moreover, by a closer inspection it can be observed that our solution provides results with less color shifting for the night time hazy scenes.

III. RESULTS AND DISCUSSION

We first tested our approach for several day-time hazy images. We use four hazy images with ground truth that are used in the

	He et al.		Meng et al		Fattal		Cai et al.		Ancuti et al.		Berman et al.		Our results	
	SSIM	CIEDE2000	SSIM	CIEDE2000	SSIM	CIEDE2000	SSIM	CIEDE2000	SSIM	CIEDE2000	SSIM	CIEDE2000	SSIM	CIEDE2000
Set 1	0.752	15.656	0.706	13.441	0.744	13.062	0.672	13.265	0.726	14.081	**0.756**	13.126	0.704	**12.386**
Set 2	0.633	20.767	0.700	16.579	0.568	20.920	0.588	19.970	0.742	14.472	0.691	17.597	**0.781**	**10.828**
Set 3	0.752	16.005	0.820	14.838	0.723	16.737	0.610	19.648	0.876	11.414	0.829	14.501	**0.871**	**10.579**
Set 4	0.617	24.836	0.790	19.568	0.539	23.428	0.608	24.043	0.763	15.763	**0.806**	16.010	0.806	**15.255**
Average	0.689	19.316	0.754	16.106	0.644	18.537	0.619	19.232	0.777	13.933	0.770	15.309	**0.791**	**12.262**

Table I. ***Quantitative evaluation.*** *Considering the four images shown in Fig.4 we compute the SSIM and CIEDE2000 indexes between the ground truth images and the enhanced results of the evaluated techniques. The hazy images, ground truth and the results are shown in Fig.4.*

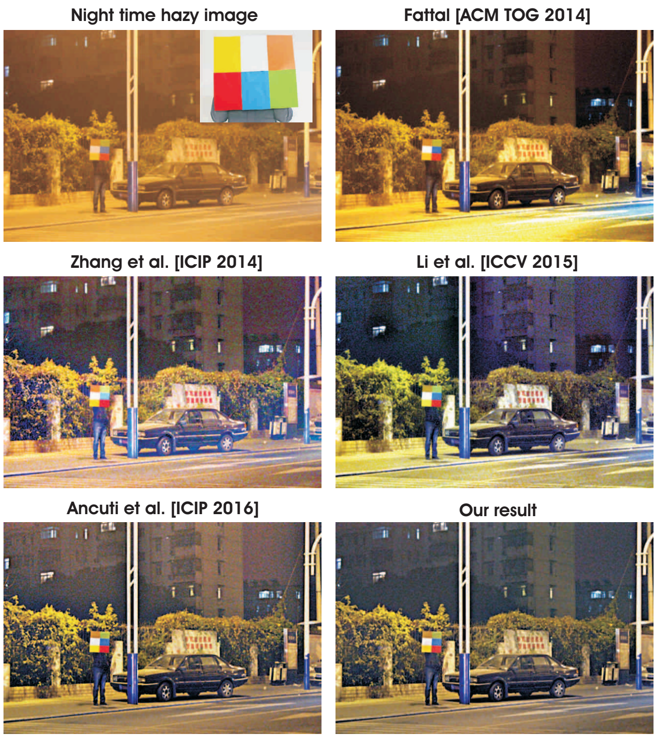

Fig. 5. **Comparative results.** *The night-time hazy image with the reference color palette (shown in the top right corner of the hazy image) is enhanced by the dehazing techniques of Fattal [11], Zhang et al. [23], Li et al. [21], Ancuti et al [24] and our approach. The Table II shows quantitative evaluation based on PSNR values.*

	yellow	white	brown	red	blue	green	**average**
Fattal	21.10	23.95	15.43	20.72	15.12	15.77	18.68
Zhang et al.	21.20	23.22	**21.30**	20.11	15.39	12.66	18.98
Li et al.	19.80	23.22	16.95	**23.39**	**17.69**	**21.10**	20.35
Ancuti et al.	27.34	30.05	18.59	23.22	17.59	17.66	22.41
Our method	**32.30**	**31.06**	18.02	21.06	16.71	17.41	**22.76**

Table II. *Based on the the results shown in Fig. 5 we compute the PSNR values as an average on RGB components for each of the 6 colors of the reference palette.*

NTIRE indoor dehazing challenge[1]. In Fig. 4 are shown the hazy images (first column), the corresponding ground truth (last column) and the dehazing results yielded by the specialized techniques of He et al. [5], Meng et al. [18], Fattal [11], Cai et al. [15], Ancuti et al. [24], Berman et al. [20] and our technique. Quantitatively, we compare directly their outcome with the ground-truth (haze free) images. In table I we show the results of structure similarity SSIM [28] and CIEDE2000 [29], [30] indexes. Qualitatively but also quantitatively it can be observed that our approach together with the techniques of Berman et al. [20] and Ancuti et al. [24] are the most competitive.

[1] http://www.vision.ee.ethz.ch/en/ntire18/

Moreover, we intensively tested our approach on the night-time images dataset introduced in [21]. The dataset contains 130 night-time hazy images with various visible light-sources colors and haze intensity.

We compare with the recent night-time dehazing techniques of Li et al. [21] and Ancuti et al. [24]. To generate the results (and those included into additional materials) we employed the original code as provided by the authors on their web-pages. Figure 6 shows comparative results based on two images of this dataset. For additional comparative results please refer to https://drive.google.com/file/d/1z-YoMqG4rq4mw7aHHifgvX7gf6l92SPp/view?usp=sharing.

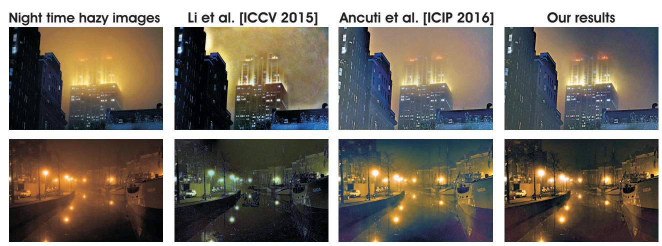

Fig. 6. **Night-time dehazing comparative results.** *From left to right: hazy images, the results of Li et al. [21], Ancuti et al. [24] and our results.*

Additionally, we performed a quantitative evaluation using the pair of images provided by Zhang et al. [23]. In Fig. 5 is shown the reference color palette and the night-time hazy image with the color palette. We compare with the dehazing techniques [11], [23], [21], [24] and compute the PSNR values for each of the 6 colors (shown in Table II). As can be seen, in average our approach performs slightly better in terms of PSNR compared with the other techniques.

To conclude, despite of its simplicity, our approach yields comparative results with the recent dehazing techniques for day-time but also for night-time hazy scenes. Another advantage of our solution is the computational efficiency. Our unoptimized Matlab implementation processes an 800×600 image in 0.9 seconds on a Dell Latitude E7450 equipped with i7 at 2.6GHz CPU and 16GB of RAM. This is almost four time faster than our fusion-based implementation [24]. On the same image, the processing time of the method of Li et al. [21] is approximately 30 seconds, the method of Zhang et al. [23] requires a similar computation as He et al. [5] (approx. 20 seconds per image) and the method of Berman et al. [20] requires approximately 8 seconds.

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