

## segmenting dark channel prior을 이용한 단일 영상에서의 안개 제거

\*Tran, Nhat Huy, \*\*Bui, Minh Trung, \*\*\*김원하

경희대학교

\*minhtrung@khu.ac.kr, \*\* huytn@khu.ac.kr, \*\*\*wonha@khu.ac.kr

## Single image dehazing using segmenting dark channel prior

\*Bui, Minh Trung, \*\*Tran, Nhat Huy, \*\*\*Kim, Wonha

Kyung Hee University

## 요약

In image dehazing, the existing transmission estimators bring out the halo artifact at boundaries unless they adopt a refinement process with the high computational complexity. We analyze how the existing transmission estimation methods suffer from the halo artifact at the boundaries and observed that the elaborate, high computational refinement processes to remove the halo effect are excessive for dehazing. On the basis of the analysis and observation, we embed a simple segmentation logic in an existing transmission estimator, which is sufficiently accurate for dehazing. The experiment verifies that the proposed method significantly reduces the halo artifact without requiring any refinement process.

## 1. Introduction

In the dichromatic model widely used for image dehazing, precision of transmission estimation is crucial for image dehazing performance. The dark channel prior (DCP) and the median DCP (MDCP) recently prevail as transmission estimation methods [1, 2]. However, the DCP does not consider the heterogeneity of regions; thus, it often encounters transmission mismatches along the boundaries, resulting in halo artifacts at these regions. To avoid these mismatches, an additional refinement process such as soft-matting and guided-filtering has been adopted [1, 4]. Although these refinements performed well, the additional computational load heavier than that of the transmission estimation process itself limits their application in actual dehazing systems. To reduce the mismatches without using any refinement, the MDCP selects the relevant value of pixel in the dominant region, thus avoiding mismatches at simple boundaries. However, the MDCP still suffers from mismatches at the corner boundaries.

In this letter, we observe that mismatches occur whenever the pixels selected by the minimum operator of the DCP or the median operator of the MDCP do not belong in the same region as the pixel where the transmission is to be estimated. Additionally, the strength of the mismatch is closely proportional to the extremity of the boundaries. From these observations, we embed a simple and fast segmentation logic in the DCP. The proposed method

significantly reduces the mismatches at the boundaries without requiring a refinement process. We call the proposed method as the segmenting dark channel prior (SDCP).

## 2. Issues in existing transmission estimators

The dehazed images are recovered using the dichromatic model as follows [1, 2]:

$$\mathbf{I}_d(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{I}(\mathbf{x}, \mathbf{y}) - \mathbf{A}}{t(\mathbf{x}, \mathbf{y})} + \mathbf{A} \quad (1)$$

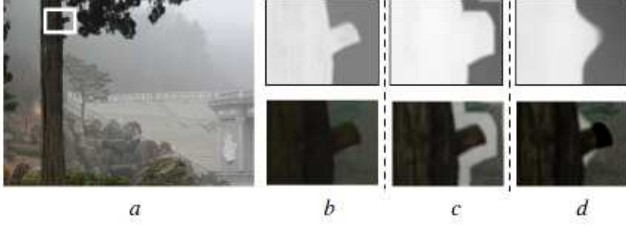
where  $\mathbf{I}_d(\mathbf{x}, \mathbf{y})$  and  $\mathbf{I}(\mathbf{x}, \mathbf{y})$  are the dehazed and hazy images, respectively.  $\mathbf{A}$  is the global atmospheric light, and  $t(\mathbf{x}, \mathbf{y})$  is the transmission value.

The DCP estimates the transmission by finding the minimum component as follows [1]:

$$\begin{aligned} t_D(\mathbf{x}, \mathbf{y}) &= 1 - w \min_{(u,v) \in \Omega(\mathbf{x}, \mathbf{y})} \left\{ \min_{c \in \{r, g, b\}} \frac{I^c(u, v)}{A^c} \right\} \\ &\equiv 1 - w \min_{(u,v) \in \Omega(\mathbf{x}, \mathbf{y})} I_m(u, v) \end{aligned} \quad (2)$$

where  $\Omega(\mathbf{x}, \mathbf{y})$  is the set of squared neighboring pixels centered at  $(\mathbf{x}, \mathbf{y})$ .  $I_m(u, v)$  is the minimum component of the normalized hazy image at  $(u, v)$ . The DCP smooths the transmission at the boundaries whenever  $\Omega(\mathbf{x}, \mathbf{y})$  covers heterogeneous regions, causing mismatches along the boundaries. Thus, a refinement process that eliminates the mismatches is desired.

To reduce the halo effect without using any refinement process, the MDCP was developed, as described by the following [2]:



**Fig. 1** Transmission maps and their dehazed images. Original hazy image (Fig. 1a), by the DCP with guide-filtering (Fig. 1b), by the DCP (Fig. 1c), by the MDCP (Fig. 1d).

$$t_M(x, y) = 1 - w \operatorname{med}_{(u,v) \in \Omega(x,y)} I_m(u, v) \quad (3)$$

By selecting the pixel value in the dominant region at  $\Omega(x, y)$ , the MDCP is better fitted to the boundary than the DCP. However, it smooths out the transmission at the corner boundaries and still suffers from the halo artifact at these boundaries.

### 3. Analysis of transmission estimation

Because DCP and MDCP use the statistical values without considering the heterogeneity of patch  $\Omega(x, y)$ , the DCP and the MDCP only well perform in a homogenous patch with smooth transmission, but they may create mismatches in patches that cover different regions.

The patches in heterogeneous regions have been reasonably assumed to cover foreground and background [2]. We separate the heterogeneous patch  $\Omega(x, y)$  into a set of foreground pixels  $\Omega^f(x, y)$  and a set of background pixels  $\Omega^b(x, y)$ . Therefore, in a heterogeneous patch,  $\Omega(x, y) = \Omega^f(x, y) \cup \Omega^b(x, y)$ ,  $\Omega^f(x, y) \cap \Omega^b(x, y) = \emptyset$  and  $\Omega^f(x, y) \neq \emptyset$ ,  $\Omega^b(x, y) \neq \emptyset$ .

We define the location  $(\tilde{x}, \tilde{y})$  of the pixel selected by either the minimum operation of the DCP or the median operation of the MDCP and distinguish it from the patch center  $(x, y)$  where the transmission is to be estimated. The value of the selected pixel is used to calculate the transmission at the patch center. Because the foreground must be darker than the hazier background, the minimum operator of DCP selects a foreground pixel. The median operator of the MDCP chooses a pixel in the dominant region of the patch. Thus, we can express the locations of the selected pixel as

$$\text{In DCP: } (\tilde{x}, \tilde{y}) \in \Omega^f(x, y)$$

$$\text{In MDCP: } (\tilde{x}, \tilde{y}) \in \begin{cases} \Omega^f(x, y) & \text{if } |\Omega^f(x, y)| \geq |\Omega^b(x, y)| \\ \Omega^b(x, y) & \text{if } |\Omega^f(x, y)| < |\Omega^b(x, y)|. \end{cases} \quad (4)$$

When the selected pixel and the patch center belong to different regions, the value that lies on the selected pixel does not represent the transmission in the patch center; hence, a mismatch is induced in the transmission [2]. Thus, for a patch that covers different regions, the DCP and MDCP can possibly create transmission mismatches. Table 1 illustrates the mismatches cases created by the DCP and MDCP in a patch that covers the background and foreground. Because the minimum operator of the DCP selects a pixel in the foreground, a mismatch occurs when the patch center is in the background. Therefore, DCP mismatches usually occur

**Table 1:** Analysis of transmission mismatches

DCP	Legend	• ×	$(x, y) \in \Omega^f(x, y), (\tilde{x}, \tilde{y}) \in \Omega^f(x, y)$	Match
		•	$(x, y) \in \Omega^b(x, y), (\tilde{x}, \tilde{y}) \in \Omega^f(x, y)$	Mismatch
MDCP	• ×	$(x, y) \in \Omega^f(x, y), (\tilde{x}, \tilde{y}) \in \Omega^f(x, y)$	Match	
	× •	$(x, y) \in \Omega^b(x, y), (\tilde{x}, \tilde{y}) \in \Omega^b(x, y)$	Match	
	×	$(x, y) \in \Omega^f(x, y), (\tilde{x}, \tilde{y}) \in \Omega^b(x, y)$	Mismatch	
	•	$(x, y) \in \Omega^b(x, y), (\tilde{x}, \tilde{y}) \in \Omega^f(x, y)$	Mismatch	

□: foreground □: background •: patch center  $(x, y)$  ×: selected location  $(\tilde{x}, \tilde{y})$  along the boundaries. The median operator of the MDCP must select the pixel in the dominant region; hence, the MDCP creates mismatches when the patch center is not in the dominant region. Thus, the MDCP mismatch usually occurs at the corner boundaries.

Fig. 1 shows the occurrences of halo artifacts in a dehazed image. As the analysis in table 1, halo artifacts exist along the boundary in the DCP transmission without a refinement and at the corner boundaries in the MDCP. The DCP transmission with a refinement using the guided-filtering

does not bring out any perceivable halo artifact.

### 4. Segmenting dark channel prior

The analysis indicates that the mismatches could be prevented by letting the selected pixel be in the same region as the patch center. To force the locations of the selected pixel and the patch center to be in the same region, we propose a method that scans the pixels only in the region that contains the patch center. By denoting the set of these pixels as  $\Omega^s(x, y)$ , the proposed method estimates the transmission as follows:

$$t_R(x, y) = 1 - w \min_{(u,v) \in \Omega^s(x,y)} I_m(u, v) \quad (5)$$

$$\text{where } \Omega^s(x, y) = \begin{cases} \Omega^f(x, y) & \text{if } (x, y) \in \Omega^f(x, y) \\ \Omega^b(x, y) & \text{if } (x, y) \in \Omega^b(x, y). \end{cases}$$

To implement (5), we construct  $\Omega^s(x, y)$  by collecting pixels in the same region as the patch center. So, the proposed method requires a segmentation process and so is called as the segmenting DCP. As known in (2), the strength of the mismatch is closely proportional to the extremity of the boundary between two regions. Therefore, although some pixels may be incorrectly segmented at unclear boundaries because the pixel values in not apparently different regions tend to be similar, the amount of mismatches should be small and the halo artifacts due to such small mismatches should be rarely apparent. From this observation, we adopt a simple and fast segmentation logic rather than the elaborate and heavily computational boundary-tracking methods, as follows:

$$\text{If } \left| \frac{I_m(u, v) - I_m(x, y)}{I_m(x, y)} \right| < \epsilon, \quad (u, v) \in \Omega^s(x, y) \quad (6)$$

where  $\epsilon$  is the segmentation threshold, and  $(u, v)$  is location of

**Table 2: Objective evaluation scores by BRISQUE**

Method	Scene	Tree	Road	Suburbs	Lake
MDCP	20.55	31.01	24.12	28.41	37.08
DCP+Guided	10.59	15.09	8.65	21.06	29.01
SDCP	10.45	15.17	8.51	21.77	28.64

neighboring pixel corresponding to patch center  $(x, y)$ . At the extreme boundary, even a roughly set value of  $\epsilon$  performs well.

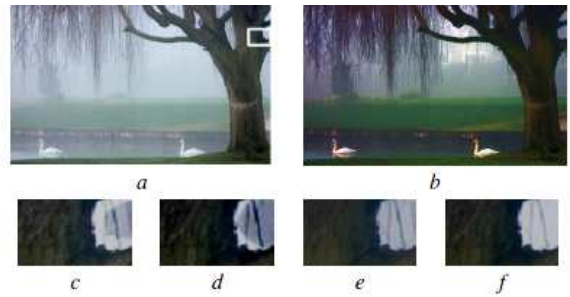
At an unclear boundary, although  $\epsilon$  is sensitive and a few pixels may be incorrectly assigned to  $\Omega_s(x, y)$ , the mismatches are not significant. Therefore, the value of  $\epsilon$  can be easily set regardless of both the boundary extremity and can be also robust to any hazy images. So, the adopted segmentation is sufficiently accurate to produce dehazed images that are free from halo artifacts.

## 5. Experiments and Discussion

In our experiments, we empirically fixed  $\epsilon$  in (6) at 0.02 for all hazy images. The patch size was set at  $15 \times 15$ . Fig. 2 shows the dehazing results when the DCP, MDCP, DCP with the guided-filtering, and the proposed SDCP are used. The DCP exhibits the halo artifact along the tree boundaries, and the MDCP shows it at the corner boundaries. However, both the DCP with the guided-filtering and the SDCP do not produce perceivable halo artifact.

For the subjective evaluation of 10 dehazed images, we invited 20 viewers and set a 95% confidence interval. The subjective-evaluation results show that the proposed method produces an almost equivalent quality as the DCP with guided-filtering as well as a noticeably better quality than the MDCP does. For the objective evaluation, we use the blind/referenceless image spatial quality evaluator (BRISQUE), which measures the possible losses in the naturalness of an image [3]. It scores from 0 to 100. A score closer to zero indicates a better image quality. Table 2 shows that the proposed method and the DCP with guided-filtering achieve the almost same scores and both are superior to the MDCP.

In terms of complexity, the advantage of the proposed method lies in the absence of an additional refinement process. Sorting requires  $O(N)$  times in complexity, where  $N$  is the total number of pixels. The complexity of the proposed method is only  $O(N)$  times, which is approximately the same as that in the DCP and MDCP. The soft-matting and the guided-filtering for refinement entail additional  $O(N^2)$  and  $O(N)$  times, respectively. Thus, the DCP with a refinement process requires additional  $O(N)$  or  $O(N^2)$  computations over the proposed method. Furthermore, the number of pixels in  $\Omega_s(x, y)$  is usually less than that in  $\Omega(x, y)$ , and the proposed method often requires less computations than the DCP and MDCP. In the execution using a 3.3GHz Pentium processor, the execution time of the proposed method is, on average, approximately the same as that of the MDCP, and requires 3% and



**Fig. 2** Original 'Lake' image (Fig. 2a), dehazed by the proposed SDCP (Fig. 2b). Comparison of dehazing results. Dehazed by the DCP (Fig. 2c), by the MDCP (Fig. 2d), by the DCP with guided-filtering (Fig. 2e) and by the SDCP (Fig. 2f)

25% of those in the DCP with soft-matting and guide-filtering refinements, respectively.

## 6. Conclusion

We have figured out that, when the patch center and the locations of the pixels selected by the operators of the DCP or the MDCP belong to different regions, the mismatches are induced in transmission estimation and also observed that the halo artifact is more severe at the extreme boundaries and is less perceivable at unclear boundaries. From these observations, we propose a transmission estimation method that embeds a simple segmentation logic into the DCP. The proposed method is verified to well remove the halo effect similar to the DCP with a refinement procedure, whereas its computational complexity is not more than that of the MDCP.

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