SINGLE IMAGE NOISE LEVEL ESTIMATION USING DARK CHANNEL PRIOR

Aziz Berkay Yeşilyurt Aybüke Erol Fatih Kamışlı A. Aydın Alatan

Department of Electrical and Electronics Engineering, Center for Image Analysis, Middle East Technical University, Ankara, Turkey

Introduction

The **dark channel prior (DCP)** has been proposed **for image dehazing** but it is observed to **change significantly under noise** (Fig. 1) as well.

In this work, **an approximate model of the dark channel pixel intensities of a noisy image** is developed and using this model, maximum likelihood estimation (MLE) is performed on the dark channel intensity values of the noisy image **to predict the noise level**.

Fig. 1. The effect of additive noise on (a) is displayed in (b). The dark channel of the noisy image (d) and the dark channel of the original image (c).

Problem Formulation

An image degraded by additive white Gaussian noise n:

$$\tilde{I} = I + n$$

Dark channel of an image I:

$$D_I(x) = \min_{y \in L(x)} \min_{c \in \{R,G,B\}} I^c(y)$$

Dark channel of a noisy image:

$$D_{\tilde{I}}(x) = \min_{y \in L(x)} \min_{c \in \{R,G,B\}} I^c(y) + n^c(y)$$

Proposed Method

Consider pixels x whose **at least one color channel** c^* is **zero**. Let ρ_d be **the fraction of the number of pixels** x satisfying $I^{c^*}(x) = 0$ to the number of all pixels that determine the corresponding dark channel pixel value d.

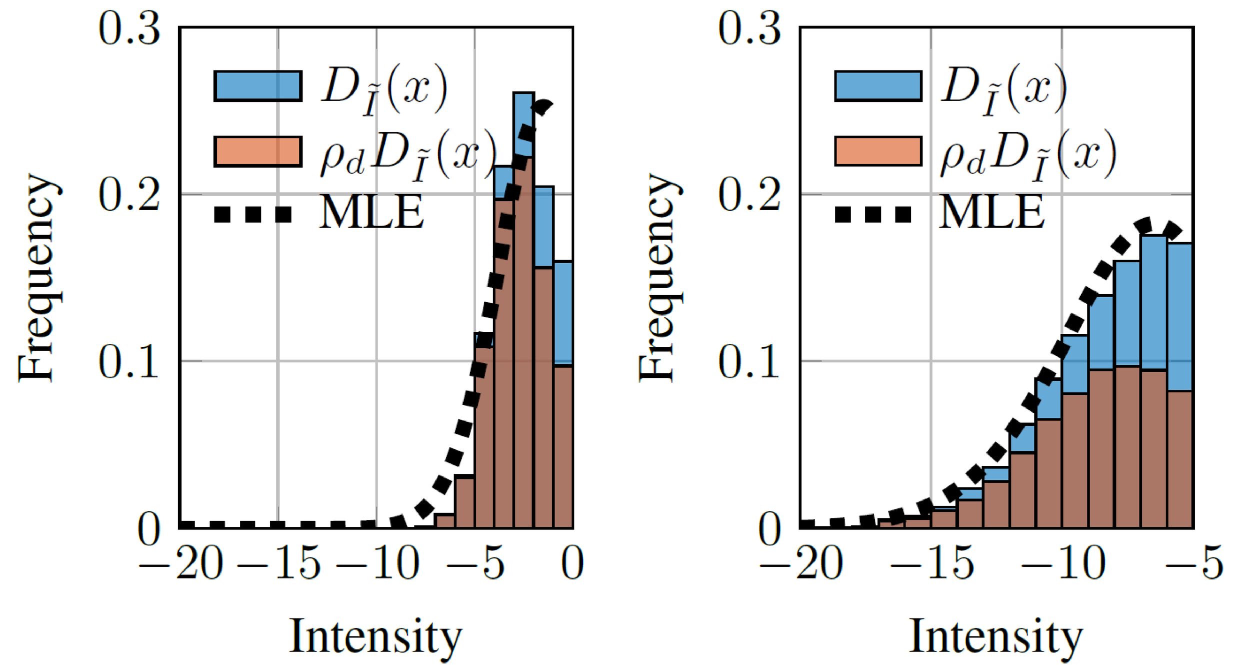

Fig. 2. The dark channel intensity values for noise levels n = 3 (left) and n = 5 (right). Blue bars are the frequency of dark channel values and red bars are the fraction of these values that come from $I^{c^*}(x) = 0$. The dashed line stands for the estimated PDFs.

For a **local patch** p, assume there exists a **sub-region** w_p inside p such that $I^{c^*}(x) = 0, \forall x \in w_p$. Assuming that original image pixels have uniform distribution, **it is more likely that the dark channel pixel value** s of p comes from a pixel $x \in w_p$ than any other pixel inside p.

$$s = \min_{y \in w_p} \min_{c \in \{R,G,B\}} n^c(y)$$

Let the cardinality of w_p be equal to k. Then, s is equal to the minimum of $w = 3k$ Gaussian noise samples and the PDF $f_S(s)$ of the random variable s can be expressed as*:

$$f_S(s; \sigma_n, w) = w f_N({}^{S}/_{\sigma_n})(1 - F_N({}^{S}/_{\sigma_n}))^{w-1}$$

where $f_N(.)$ and $F_N(.)$ denote the PDF and CDF of standard normal distribution. Now, MLE can be used to predict the noise level (Ω shows the set of all small dark channel values s w.r.t. a threshold T):

$$\begin{bmatrix} \hat{\sigma}_n \\ \hat{w} \end{bmatrix} = arg \max_{\sigma_n, w} \prod_{s \in \Omega} f_S(s; \sigma_n, w)$$

Experimental Results

Table 1. Noise estimation results on the Berkeley Segmentation Dataset (100 images at 481 × 321 resolution), showing the average and the standard deviation of the estimated noise levels and RMSE between the estimated and true noise level.

True	Liu [11]			Pyatykh [12]			Proposed Method		
Noise Level	Average	Std. Dev.	RMSE	Average	Std. Dev.	RMSE	Average	Std. Dev.	RMSE
1	1.068	0.127	0.144	1.547	0.795	0.881	1.039	0.261	0.263
5	5.001	0.117	0.117	5.214	0.347	0.404	5.232	1.159	1.182
10	10.011	0.193	0.193	10.203	0.265	0.333	10.539	1.859	1.935
15	15.004	0.214	0.214	15.172	0.263	0.314	15.075	2.319	2.320
20	19.980	0.231	0.231	20.126	0.333	0.355	20.195	2.361	2.369
25	24.955	0.256	0.260	25.063	0.391	0.396	26.414	3.175	3.475

Table 2. Noise estimation results on the high resolution DIV2K dataset (50 images at 2040 × 1356 resolution), showing the average and the standard deviation of the estimated noise levels and RMSE between the estimated and true noise level.

True	Liu [11]			Pyatykh [12]			Proposed Method		
Noise Level	Average	Std. Dev.	RMSE	Average	Std. Dev.	RMSE	Average	Std. Dev.	RMSE
1	1.434	0.948	1.042	1.344	0.540	0.598	1.160	0.465	0.492
5	5.225	0.532	0.578	4.907	0.240	0.260	5.087	0.871	0.876
10	10.172	0.354	0.393	9.846	0.326	0.362	10.196	1.129	1.146
15	15.152	0.286	0.324	14.761	0.464	0.525	15.079	1.023	1.026
20	20.146	0.260	0.298	19.686	0.544	0.630	19.650	1.644	1.681
25	25.138	0.250	0.285	24.644	0.571	0.675	25.506	2.050	2.111

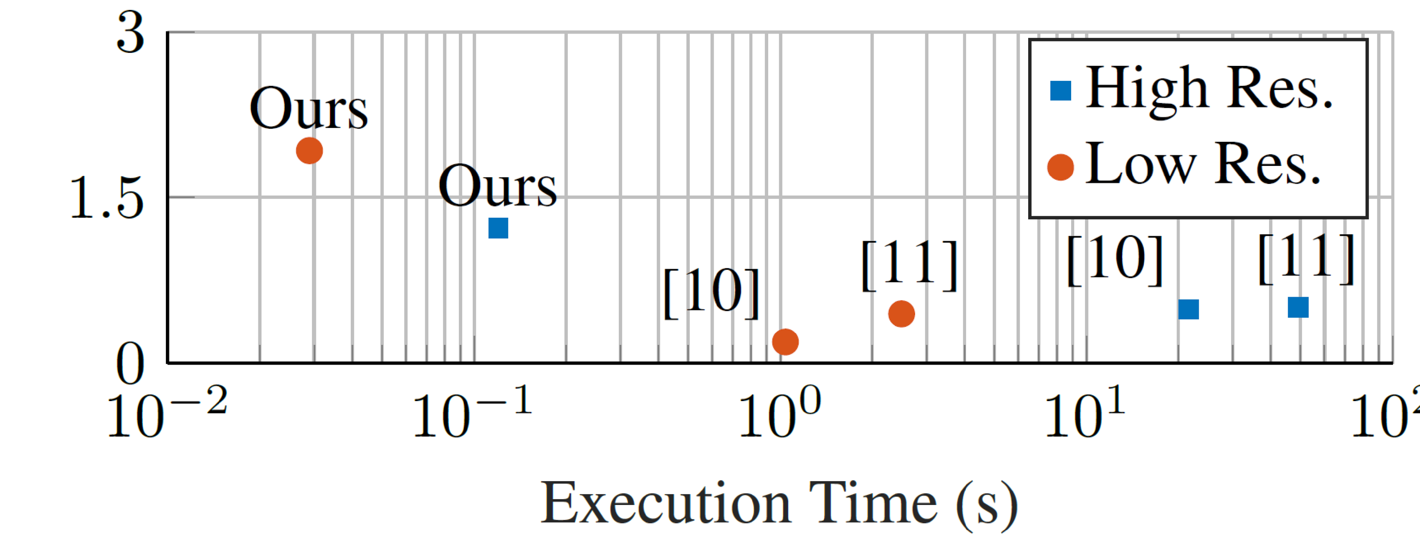

Fig.3. Performance of the proposed algorithm for **low resolution and high resolution image datasets** compared with Liu *et al.*, 2013 [10] and Pyatykh *et al.*, 2013 [11] with respect to execution time and RMSE.

Conclusion

The proposed method performs **faster than the state-of-the-art methods by two orders of magnitude** while providing **slightly inferior accuracy of estimation**. The noise is assumed to be AWGN, but similar models can be derived for other types.

*: B. C. Arnold *et al.*, A First Course in Order Statistics, 2008