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.

Problem Formulation

An image degraded by additive white Gaussian noise \( n \):
\[
\mathbb{I} = \mathbb{I} + n
\]

Dark channel of an image \( \mathbb{I} \):
\[
D_\mathbb{I}(x) = \min_{y \in L(x)} \mathbb{I}(y)
\]

Dark channel of a noisy image:
\[
D_{\mathbb{I}}(x) = \min_{y \in L(x)} (\mathbb{I}(y) + n^2)
\]

Proposed Method

Consider pixels \( x \) whose at least one color channel \( c \) is zero. Let \( \mathcal{Y}_d \) 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 \( d \).

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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 \( p \).

\[
S = \min_{y \in \mathbb{I}} \min_{w \in w_p} n^2(y)
\]

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:
\[
f_S(s; \sigma_n, w) = w f_N(s; \sigma_n, w^{-1})(1 - F_N(s; \sigma_n, w)^{w-1})
\]

where \( f_N(\cdot) \) and \( F_N(\cdot) \) denote the PDF and CDF of standard normal distribution. Now, MLE can be used to predict the noise level (\( \Omega \) shows the set of all small dark channel values \( s \) w.r.t. a threshold \( T \)):
\[
\hat{\sigma}_n^{\omega} = \text{arg} \max_{\sigma_n, w} \prod_{s \in \Omega} f_S(s; \sigma_n, w)
\]

Experimental Results

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.

Table 1. Noise estimation results on the Berkeley Segmentation Dataset (100 images at 491 x 521 resolution), showing the average and the standard deviation of the estimated noise levels and RMSE between the estimated and true noise level.

<table>
<thead>
<tr>
<th>Noise Level</th>
<th>Average</th>
<th>Std. Dev.</th>
<th>RMSE</th>
<th>Average</th>
<th>Std. Dev.</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>True</td>
<td>1.08</td>
<td>0.125</td>
<td>0.144</td>
<td>1.54</td>
<td>0.751</td>
<td>0.061</td>
</tr>
<tr>
<td>Liu [10]</td>
<td>1.00</td>
<td>0.015</td>
<td>0.017</td>
<td>0.32</td>
<td>0.347</td>
<td>0.044</td>
</tr>
<tr>
<td>Pyatykh et al. [11]</td>
<td>1.00</td>
<td>0.01</td>
<td>0.015</td>
<td>0.32</td>
<td>0.347</td>
<td>0.044</td>
</tr>
</tbody>
</table>

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

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