Final Project on Low Illumination Image Enhancement

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***Abstract*—In this paper, we reproduce a method of nighttime low-illumination image enhancement based on the use of bright and dark channels. Our starting point is an RGB image (I) with which we obtain a first approximation of the transmission (t) based on the bright channel (I^{bright}). Then we use the dark channel (I^{dark}) to correct errors in the initial transmission estimate. Next, we apply a guided filter to improve the transmission. Finally, we obtain the well-exposed image (J) from the original image, the transmission, and an atmospheric light estimation (A). In the results obtained, we observe a clear improvement in the image's exposure.**

***Index Terms*—Image enhancement, bright and dark channel, transmission, atmospheric light, guided filter.**

I. Introduction

CLEAR visualization of images taken under low light conditions is a challenge that affects many aspects of our lives. Underexposed images can obscure critical details, complicating the interpretation of a scene. A solution to this problem has wide-ranging implications, from improving security camera footage for law enforcement to photographs taken by a person on their smartphone.

The objective is coding a method that enhances image quality based merely on the information form the original RGB image. This paper focuses on reproducing a technique [1] for nighttime low illumination image enhancement through the use of bright and dark channels. It is necessary to mention that our code does not follow exactly the same steps as the original method. The variations are explained in their corresponding sections.

We were drawn to this topic by the closeness of its applications to our lives. In the present day, we take photographs regularly and in many cases there is no adequate lighting. For this reason, we have opted to implement this method, as it can be used with our own original images. Furthermore, we find it interesting to be able to obtain more visual information simply by a single image processing. In many cases additional information is used like infrared images or techniques such as High Dynamic Range Imaging [2], in which images captured at different exposure levels are combined.

II. Method

The exposure model of an RGB image ($\mathbf{I}$) can be expressed by

$$\mathbf{I}(x) = \mathbf{J}(x)t(x) + \mathbf{A}(1 - t(x)) \tag{1}$$

where $\mathbf{J}(x)$ is the scene radiance (i.e., the well exposed image), $\mathbf{A}$ is the global atmospheric light, and $t(x)$ is the medium transmission. The bold font indicates that there are different values for each channel, and $f(x)$ corresponds to the value of f at pixel x.

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Our goal is to find $\mathbf{J}(x)$ by applying

$$\mathbf{J}(x) = \frac{\mathbf{I}(x) - \mathbf{A}}{t(x)} + \mathbf{A}. \tag{2}$$

For this we need to find a good approximation for $\mathbf{A}$ and $t(x)$.

A. Bright and dark channels

We start by obtaining the the bright (I^{bright}) and dark (I^{dark}) channels of our input image $\mathbf{I}(x)$

$$I^{dark}(x) = \min_{c\in\{R,G,B\}} \left(\min_{y\in\Omega(x)} (I^c(y)) \right) \tag{3}$$

$$I^{bright}(x) = \max_{c\in\{R,G,B\}} \left(\max_{y\in\Omega(x)} (I^c(y)) \right) \tag{4}$$

where $I^c(x)$ is a color channel of $\mathbf{I}(x)$, $\Omega(x)$ is a local patch centered at x and y is a pixel in said patch.

Fig. 1. Example of dark (left) and bright (right) channels.

For a haze-free image (i.e., all the light reaches the objective and is therefore well illuminated), $I_{\text{dark}}(x) \to 0$. Besides, in a properly exposed image the intensity of $I_{\text{bright}}(x)$ is consistently high, tending to 255 (or 1 if the image is normalized).

B. Atmospheric light estimation

The next step is to calculate the atmospheric light estimation. To do this we select the top 10% brightest pixels in $I^{bright}(x)$. Next, we look at the value of these pixels in the corresponding channel of the original image I^c and calculate the mean. This way we obtain the atmospheric light of that channel A^c. We should obtain a 3-element array since this process is done to each channel of the image. Therefore:

$$\mathbf{A} = [A^R, A^G.A^B] \tag{5}$$

C. Initial transmission estimation

For an initial transmission estimation, we start from (1) and apply two maximum filter to each side, one for the channel and one for the patch $\Omega(x)$.

$$\max_c \left(\max_{y \in \Omega(x)} (I^c(y)) \right) = t(x) \max_c \left(\max_{y \in \Omega(x)} (J^c(y) \right) + (1 - t(x)) \max_c (A^c) \tag{6}$$

We have assumed that in the small local patch $\Omega(x)$ the transmission is a constant. We can rewrite (6) as

$$I^{bright}(x) = t(x) J^{bright}(x) + (1 - t(x)) \max_c (A^c) \tag{7}$$

As we mentioned, the J^{bright} should tend to 1 for a normalized image

$$I^{bright}(x) = t(x) + (1 - t(x)) \max_c (A^c) \tag{8}$$

Isolating $t(x)$ and renaming it $t_{bright}(x)$ we obtain

$$t^{bright}(x) = \frac{I^{bright}(x) - \max_c(A^c)}{1 - \max_c(A^c)} \tag{9}$$

We take $t^{bright}(x)$ as an initial transmission estimation.

To obtain $t^{dark}(x)$ we can follow the same procedure but instead of applying a max operator, we use min:

$$\min_c \left(\min_{y \in \Omega(x)} (I^c(y)) \right) = t(x) \min_c \left(\min_{y \in \Omega(x)} (J^c(y) \right) + (1 - t(x)) \min_c (A^c) \tag{10}$$

$$I^{dark}(x) = t(x) J^{dark}(x) + (1 - t(x)) \min_c (A^c) \tag{11}$$

In this case, the J^{dark} should tend to 0 for a normalized image

$$I^{dark}(x) = (1 - t(x)) \min_c (A^c) \tag{12}$$

When we isolate $t(x)$, and renaming it $t_{dark}(x)$, we obtain

$$t^{dark}(x) = 1 - \frac{I^{dark}}{\min_c(A^c)} \tag{13}$$

There is alternative to obtain t^{dark} that was found on [3]. The authors of this paper propose that, considering (1) as 3 equations (one for each channel), we divide them by A^c and then apply the two minimum filters on each side. Taking into account that $J^{dark} \to 0$, when applying the minimum we obtain the following equation

$$t^{dark}(x) = 1 - \min_c \left(\min_{y \in \Omega(x)} \frac{I^c}{A^c} \right). \tag{14}$$

In our code we have decided to use (13) since it is in accordance with the definition of t^{bright}.

D. Corrected transmission

When a patch contains a bright object the previous estimation $t_{bright}(x)$ will be inaccurate. Thus the dark channel is employed to refine erroneous transmission estimates derived from the bright channel.

The first step is to compute

$$I^{difference}(x) = I^{bright}(x) - I^{dark}(x). \tag{15}$$

We define

$$t^{corrected}(x) = t^{bright}(x) \cdot t^{dark}(x) \tag{16}$$

To calculate the refined transmission we take the value of $t^{corrected}$ when $I^{difference}$ is lower than a threshold α, otherwise the pixel takes the t^{bright} value.

$$t(x) = \begin{cases} t^{corrected}(x) & \text{if } I^{difference}(x) < \alpha \\ t^{bright}(x) & \text{otherwise} \end{cases} \tag{17}$$

E. Transmission guided filtering

The transmission map tends to undergo a loss of edge information. Therefore, a guided filter technique is applied to refine $t(x)$ and maintain the edge information of the input image. We found that the original paper [1] provided limited information about this procedure and some inconsistencies with [4]. After trying different processes we have decided to follow the next interpretation [4] with which we obtain the best results.

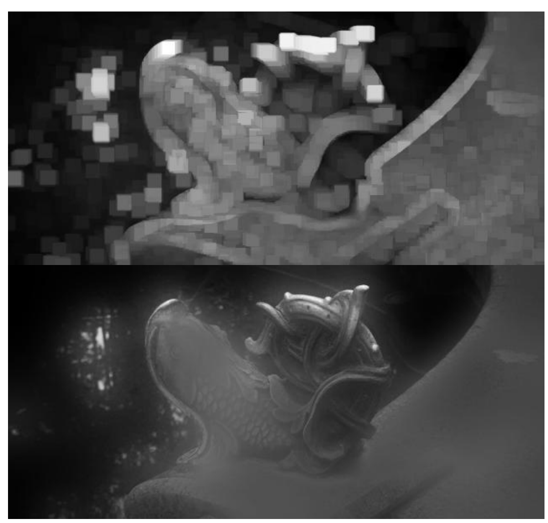

Fig. 2. Transmission before (top) and after (bottom) the guided filter.

In guided filtering, the primary concept is to filter an input image p while considering a guidance image I to obtain the final image q. In this case our interest is to filter the transmission map $t(x)$ with the RGB $\mathbf{I}(x)$ as the guidance image. The final result can be expressed as

$$q_i = \bar{\mathbf{a}}_i^T \mathbf{I}_i + \bar{b}_i \tag{18}$$

where $\mathbf{a}_i$ and b_i are a vector and a constant coefficients respectively. The subscript i indicates the pixel. The coefficients are calculated following

$$\mathbf{a}_k = (\Sigma_k + \epsilon U)^{-1} \left(\left(\frac{1}{|w|} \sum_{i \in w_k} \mathbf{I}_i p_i \right) - \boldsymbol{\mu}_k \bar{p}_k \right) \tag{19}$$

$$b_k = \bar{p}_k - \mathbf{a}_k^T \boldsymbol{\mu}_k \tag{20}$$

where w_k is a window centered at the pixel k, Σ_k is the 3×3 covariance matrix of $\mathbf{I}(k)$, U is a 3×3 identity matrix, ϵ is the regularization parameter (used to determine the intensity of the changed pixels), $\boldsymbol{\mu}_k$ is the average value of $\mathbf{I}$ in w_k, $|w|$ is the number of pixels in w_k, and $\bar{p}_k = \frac{1}{|w|} \sum_{i \in w_k} p_i$ is the mean of p in w_k.

One of the inconsistencies we found is that according to [1]

$$t(k) = a_k t^{corrected}(k) + k_k. \tag{21}$$

This leads to understand that $t^{corrected}$ is the guidance image. In reference [1] the guided filter is explained for the case in which both p and I are 2-D images. We tried this version using $p = t$ and $I = Luma$ and vice versa but the outcomes were poor, so we chose to continue with the other approach.

Regarding (18), when calculating $\bar{\mathbf{a}}_i$ there are two possibilities. The first one is to calculate the average of each channel separately, i.e., $\bar{\mathbf{a}}_i = [\bar{a}_i^R, \bar{a}_i^G, \bar{a}_i^B]$. The second option is to calculate the average without separating the channels. In this case the values of the 3 channels are combined in the process. We opted for the first method although the results are similar.

F. Final image

Once we obtain the best approximations for $\mathbf{A}$ and $t(x)$ we can now calculate the final image

$$\mathbf{J}(x) = \frac{\mathbf{I}(x) - \mathbf{A}}{\max(t(x), t_0)} + \mathbf{A}. \tag{22}$$

The parameter t_0 is introduced to limit $t(x)$ to a lower bound and it's value is assigned through experimental analysis. This way, we avoid introducing noise to the radiance $\mathbf{J}$, which occurs when the values of $t(x)$ tend to zero.

To represent the image information the values must be normalized. After operating, the range is outside the desired one ($0 - 1$ or $0 - 255$). To correct it we apply

$$\mathbf{J} = \mathbf{J} - \min(\mathbf{J}) \tag{23}$$

$$\mathbf{J} = \frac{\mathbf{J}}{\max(\mathbf{J})} \tag{24}$$

This way we obtain a normalized final image

III. Results

A. Parameters setting

Consider an input image of approximately 700 to 1200 pixels per side, we have calculated the bright and dark channels with a patch $\Omega(x) = 15 \times 15$. For the transmission correction he threshold $\alpha = 0.4$ Regarding the guided filter, ϵ was set to 0.001 and $w_k = 50 \times 50$. The window size w_k is high to keep the edge information. To obtain the final picture $t_0 = 0.1$.

B. Images Results

We tested this algorithm with several images. Below we show some examples before and after applying it.

Fig. 3. Photograph by Nikhil More, distributed under a CC BY-SA 4.0 license.

Fig. 4. Photograph by Mykyta Kondratov, distributed under a Unsplash license.

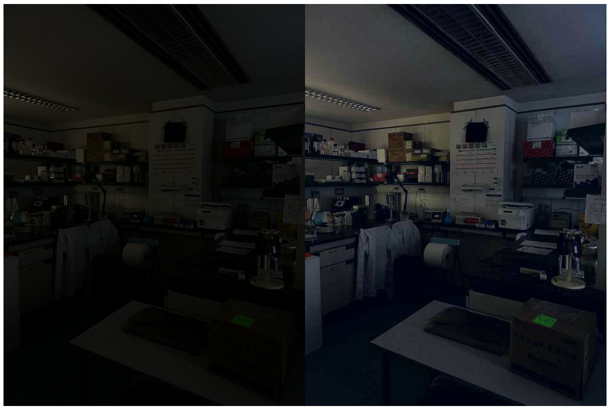

Fig. 5. Laboratory. Original Image.

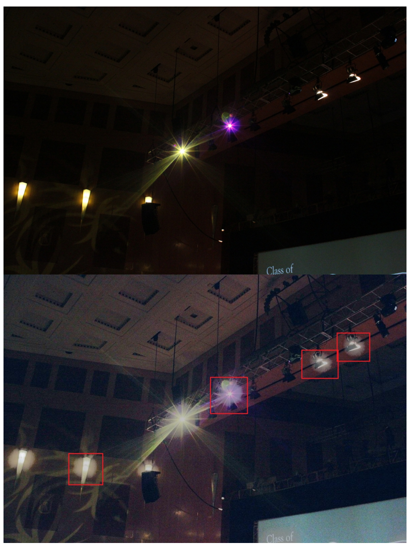

Fig. 6. Lights. Original Image. The withe blurs in the light sources are boxed.

Fig. 7. Plant. Original Image.

We can see that the method is effective and there is a clear improvement in the images. However, we notice the results show a higher amount of noise.

In general the processed images maintain color fidelity, but sometimes there is a certain distortion. In Fig. 6 it is noticeable a subtle blue tint on the result image.

Regarding the code execution time, it is approximately $1-2s$ for the images considered (about 700 to 1200 pixels per side). It increases with picture dimensions.

TABLE I
RUNNING TIME FOR DIFFERENT IMAGE DIMENSIONS.

Image dimensions (px)	**Running time** (s)
303×640	0.8919312953948975
427×640	1.0675463676452637
480×640	1.3200943470001220
975×731	1.8505971431732178
800×1200	2.1578121185302734

With images that have specific light sources (Fig. 6) we notice the method blurs that area with a white spot.

IV. Conclusion

In this paper, we reproduce a technique [1] for nighttime low illumination image enhancement via the bright and dark channels. Our approach diverges mainly on the use of the guided filter from the original method.

The results show that the code is efficient in improving the visibility of low-light images. However, the running time increases with the image size. Moreover, it must be considered adapting the value of the different parameters to the picture dimensions, which has to be done manually.

For a future project we would like to focus on improving the technique's performance on images with specific light focal points, as these areas tend to exhibit blurring.

References

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Note: AI tools were used for strengthening our wording.