



An Implementation of a Nighttime Image Enhancement Algorithm, based on Bright/Dark Channel Prior

OpenGL Application

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Chapter 1

Subject Specification

1.1 Objective

The goal of this project is to implement an algorithm for enhancing nighttime images, and study its pro's and con's, considering the quality of the final image and the computational resources required for running the algorithm.

1.2 Background

Enhancing nighttime, low-illumination images is a basic challenge of image processing. Images captured in nighttime low illumination are not only less pleasing to the human eye, but also create additional difficulties if the image has to be further processed for computer vision applications.

There are several approaches available for enhancing nighttime images:

- most of them rely on **fusing together multiple images in a point-to-point way**. Whereas these methods were shown to be effective, they are not applicable if one doesn't have multiple images at hand.
- there are some **single-image methods** as well (e.g. histogram equalization, wavelet transform, Single Scale Retinex, Multi Scaler Retinex, ...), but they all have some significant flaws: they usually amplify noise and over-enhance the contrast.
- Lately, some **dark-channel-based methods and bright-channel-based methods** were developed, with the goal of reaching and adaptive improvement of contrast and estimating the local exposure for under-exposed images, respectively, but the former usually suffer from bright spots whereas the latter are generally too sensitive to bright light.

For this project, a relatively new single-image method was selected, which utilizes both the dark- and the bright-channel prior, to combine the advantages of both types of methods. The method was proposed by Zhenghao Shi, Mei mei Zhu, Bin Guo, Minghua

Zhao and Changqing Zhang, in a research article entitled 'Nighttime low illumination image enhancement with single image using bright/dark channel prior', originally published in the EURASIP Journal on Image and Video Processing volume 2018, Article number: 13 (2018). The article can be accessed here.

Chapter 2

The algorithm

In this section I will summarize the algorithm proposed by Zhenghao Shi, Mei mei Zhu, Bin Guo, Minghua Zhao and Changqing Zhang.

2.1 Overview

The key idea of the algorithm can be summarized in the formula (2.1)

$$I(x) = J(x) * t(x) + A * (1 - t(x)) \quad (2.1)$$

where

- J is the well-exposed output image
- I is the low-illumination input image
- A is the global atmospheric light
- t is the transmission map, showing what portion of light is not scattered and reaches the camera
- x is a pixel of the image

This formula states that the low-illumination image, that we have as input, is a linear combination of the well-exposed image and the global atmospheric light, where the weight of the well-exposed image is the transmission coefficient.

After a simple transformation, (2.1) can be rewritten as

$$J(x) = \frac{I(x) - A}{t(x)} + A \quad (2.2)$$

With I being known, the algorithm basically attempts to approximate A and t , to finally obtain an approximation of J , based on (2.2).

2.2 Background

As the title suggests, the algorithm relies on the bright- and dark-channel priors to approximate the transmission map t . These priors can be defined as:

- $I^{dark}(x)$
= the dark-channel prior in pixel x = the lowest color (R, G or B) intensity in any of the pixels in the patch ($n \times n$) centered around the pixel x
- $I^{bright}(x)$
= the bright-channel prior in pixel x = the highest color (R, G or B) intensity in any of the pixels in the patch ($n \times n$) centered around the pixel x

It is important to note, that for a haze-free, good-illumination image we expect that

$$I^{dark}(x) \rightarrow 0$$

and

$$I^{bright}(x) \rightarrow 255$$

2.3 Steps

1. Obtain the bright and dark-channel priors of the input low-illumination image
 - using max- and min-filters
2. Approximate the global atmospheric light A
 - approximates as the average intensity of the top 10% brightest pixels in the bright channel
3. Get an initial transmission map t^{bright} based on the bright-channel prior
 - Based on the approximations
 - (a) $I^{bright}(x) \rightarrow 255$
 - (b) the transmission $t(x)$ is constant in a small local patch around x
 - we can deduce that

$$t(x)^{bright} = \frac{I^{bright}(x) - A^c}{255 - A^c} \quad (2.3)$$
 - But this transmission map estimation has some flaws, which will be resolved in the next step:
 - the estimation will fail when there is a bright object entirely contained by a patch

- transmission driven rather by object/region texture instead of nighttime properties
4. Get a corrected transmission map $t^{\text{corrected}}$, based on a correction relying on the dark-channel prior

- first, using the assumptions

$$(a) I^{\text{dark}}(x) \rightarrow 0$$

- (b) the transmission $t(x)$ is constant in a small local patch around x
compute t^{dark} by

$$t(x)^{\text{dark}} = \frac{I^{\text{dark}}(x) - A^c}{0 - A^c} = 1 - \frac{I^{\text{dark}}(x)}{A^c} \quad (2.4)$$

- then,

- for any pixel x , where $I^{\text{bright}}(x) - I^{\text{dark}}(x) < \text{Threshold}$

- * consider the transmission t^{bright} to be unreliable, and correct it as

$$t^{\text{corrected}}(x) = t^{\text{bright}}(x) * t^{\text{dark}}(x) \quad (2.5)$$

- for any other pixel, use

$$t^{\text{corrected}}(x) = t^{\text{bright}}(x) \quad (2.6)$$

- This corrected transmission map

- shows structures that would have been missed by the bright-only-based enhancement
- due to minimum-filtering for the dark channel, the method suffers from loss of edge information, thus resulting in an image which seems to be composed of patches and suffers from the halo effect. These issues will be resolved in the next step.

5. Refine the corrected transmission map using guided filtering

- the details of guided filtering are considered out of scope here
- the advantage of applying guided filtering is that it helps to
 - capture sharp edge discontinuities
 - outline the profile of the objects

6. Recover the scene radiance, based on the refined transmission map t

- Apply (2.2), with a small modification to avoid noise: restrict $t(x)$ to a lower bound t_0

$$J(x) = \frac{I(x) - A}{\max(t(x), t_0)} + A \quad (2.7)$$

Chapter 3

Implementation

The algorithm was implemented in C++, using OpenCV, in an object-oriented manner. Thus, most steps of the algorithm are separated in their own class, and in some cases, multiple implementations for the same step were provided. By applying the strategy design pattern, these implementations can be easily switched and compared.

3.1 Step 1: Obtain the bright and dark-channel priors of the input low-illumination image

First, a Minimum and Maximum operator for uchar pixels, both extending the same ChannelIntensityOrderOperator abstract class were implemented.

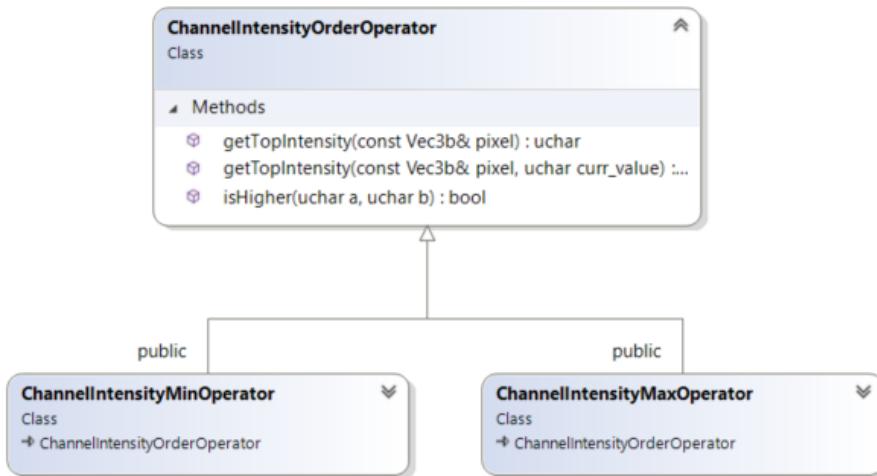


Figure 3.1: The Minimum and Maximum operators for pixels

Then, two implementations of PatchOrededFilter were provided to apply such a `ChannelIntensityOrderOperator` on an image, to find the 'top' (the minimum or maximum, depending on the injected `ChannelIntensityOrderOperator`) value for each patch centered at x:

- the brute-force implementation for each pixel x , traverses all the $w * w$ pixels in the patch around x to compute the top value at x . The overall complexity is $O(n*m*w^2)$, where $n*m$ is the size of the image, and w is the width of the patch.
- the dynamic-programming based implementation first performs a row-based aggregation ($\text{filtered_row}[x][y] =$ the top intensity in the segment of length w in the row x , centered at column y) and then a column based aggregation ($\text{filtered_col}[x][y] =$ the top value of filtered_row in the segment of length w in the column y , centered at row x), based on the observation that the filtering operation is linearly separable. By applying a further optimization to easily find the top intensity of a segment based on the top intensity of the previous segment, via an ordered Queue, we can reach the final complexity of $O(n*m)$ (with a multiplicative constant of 4).

A PatchOrderedFilter with the corresponding ChannelIntensityMinOperator or ChannelIntensityMaxOperator implements a Minimum- or Maximum-Filter on an image. Thus, it allows us to compute the Bright- and Dark-Channel of an image.



Figure 3.2: The Minimum and Maximum filters, for computing the Bright- and Dark-channels, implemented by a PatchOrderedFilter.

3.2 Step 2: Approximate the global atmospheric light A

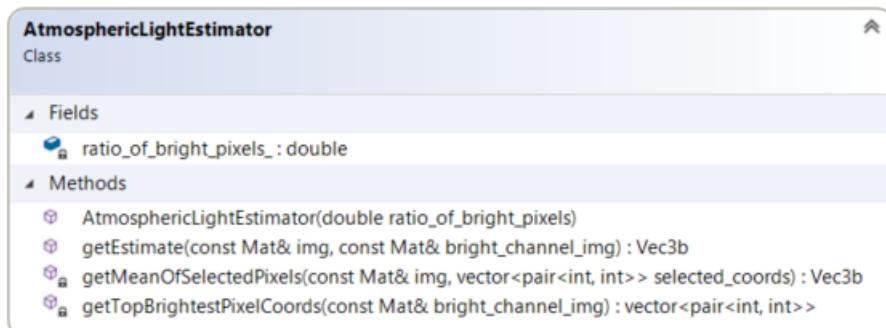


Figure 3.3: The class for approximating the global atmospheric light A of an image

The AtmosphericLightEstimator computes an approximation based on the formula specified above. However, since sorting all the bright-channel intensities would be an expensive operation (for an $n \times m$ image, the complexity is $O(n \times m \times \log(n \times m))$), a multimap was used to keep track of the top 10% of the brightest bright-channel values (a mapping from their brightness to their coordinates) only while scanning the image. After the whole image was scanned and the final top 10% brightest bright-channel values were found, a mean operation was applied on the intensity of the pixels at the selected coordinates.

3.3 Steps 3-5: Estimate the transmission map t

Since the algorithm requires 3 estimates to be computed for the transmission map t (since they are built on top of each other), the classes for computing the estimates are all based on the same interface.



Figure 3.4: The estimators for the transmission map

3.4 Step 3: Get an initial transmission map t^{bright} based on the bright-channel prior



Figure 3.5: The transmission map estimator relying on the bright channel only

3.5 Step 4: Get a corrected transmission map $t^{\text{corrected}}$, based on a correction relying on the dark-channel prior



Figure 3.6: The transmission map estimator relying on both the bright- and dark channels

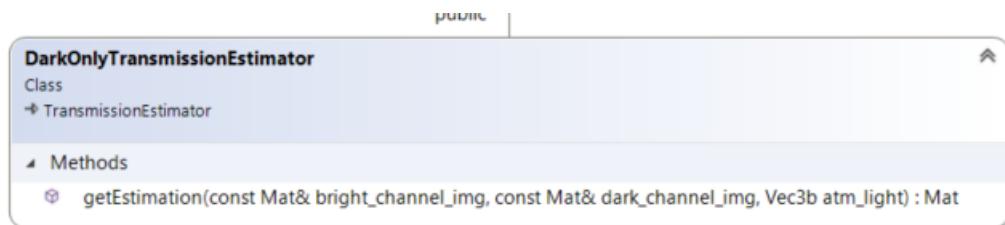


Figure 3.7: The helper estimator, relying on the dark-channel only

3.6 Step 5: Refine the corrected transmission map using guided filtering

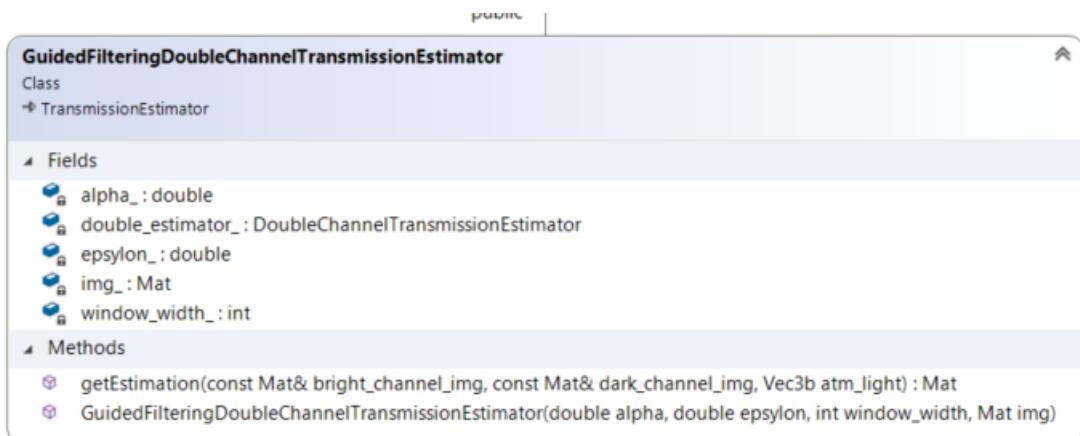


Figure 3.8: The final transmission estimator, that relies on a DoubleChannelTransmissionEstimator and on a GuidedFilter

The helper class of the final estimator is a GuidedFilter. Note that the GuidedFilter was not implemented based on a direct translation of the formulas in the presented research article, but rather on a simplified algorithm presented on Wikipedia.



Figure 3.9: The GuidedFilter

3.7 Step 6: Recover the scene radiance, based on the refined transmission map t

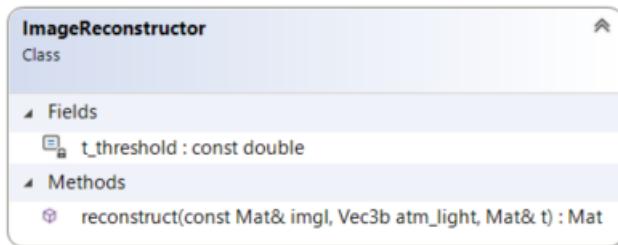


Figure 3.10: The class that reconstructs the well-exposed image from the original image, the atmospheric light estimation and the transmission map estimation

Appendix A

Good Results



(a) The Original Image



(b) Bright-channel Enhanced Image



(c) Enhanced Image using both Channels



(d) Final Enhanced Image (Guided)

Figure A.1: Sample Results: fruits. Notice how some fruits in the (b) and (c) images are "glowy" (e.g. the banana), and some fruits in image (b) are too bright, losing their original color (e.g. the peach). Moreover, in images (b) and (c) we can see that the image is severely "patchy" (e.g. in the tea cup's zone). All these issues are later resolved in image (d).



(a) The Original Image



(b) Bright-channel Enhanced Image

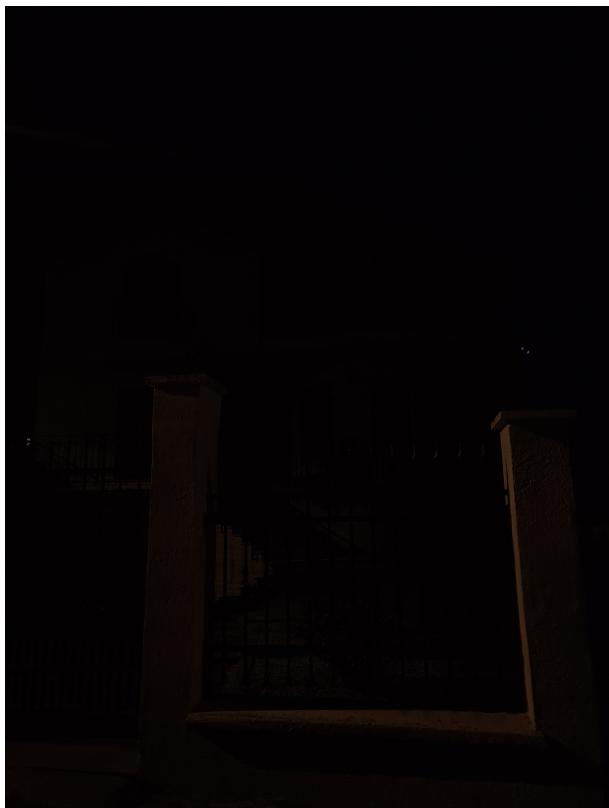


(c) Enhanced Image using both Channels



(d) Final Enhanced Image (Guided)

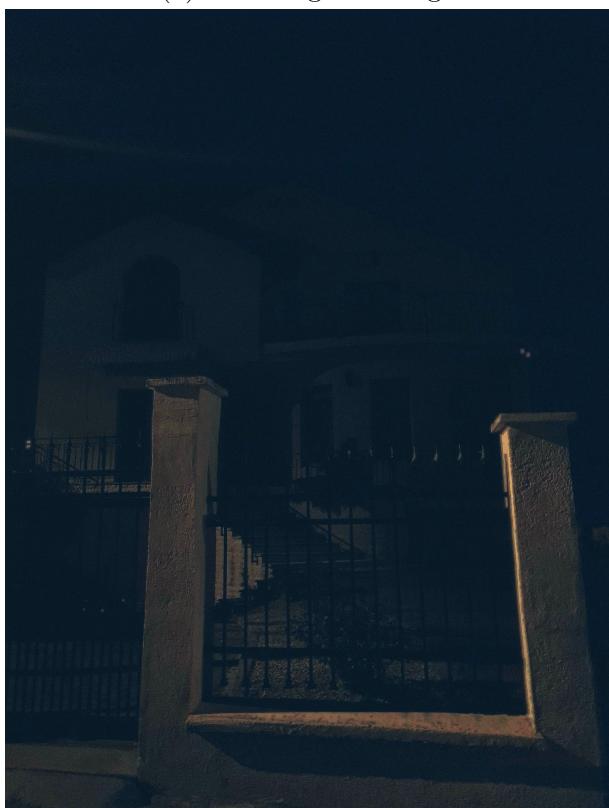
Figure A.2: Sample Results: city. Notice how the patches at the stars are resolved by the guided filtering in image (d).



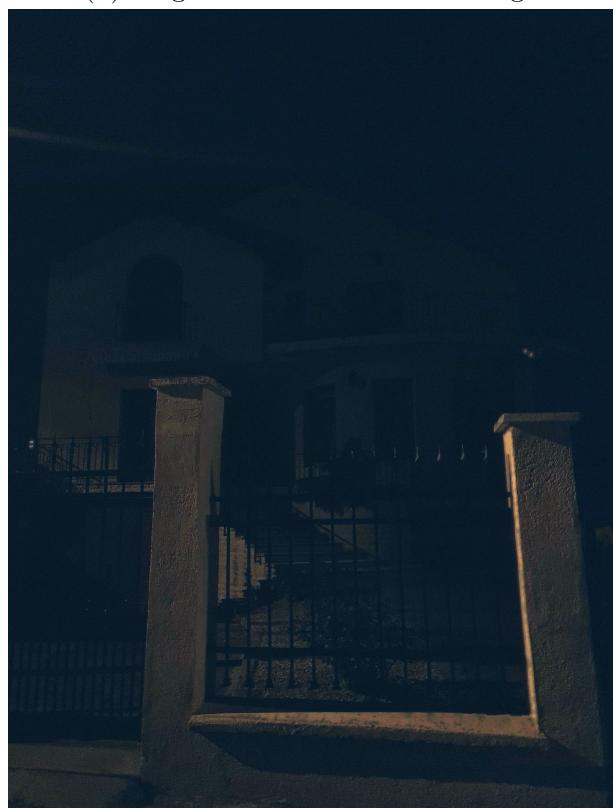
(a) The Original Image



(b) Bright-channel Enhanced Image



(c) Enhanced Image using both Channels

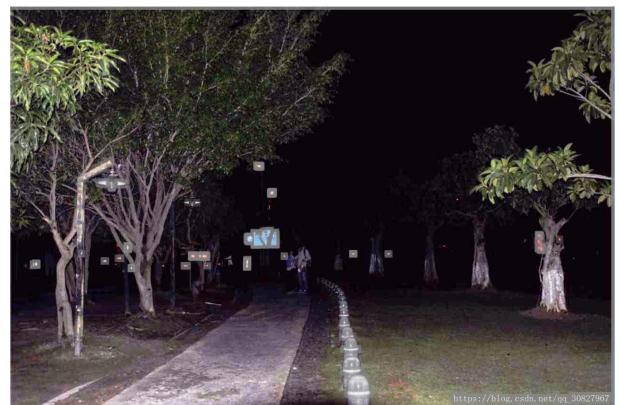


(d) Final Enhanced Image (Guided)

Figure A.3: Sample Results: a house with a fence in Cluj (photo taken by me). Note that the final image is till undoubtedly better than the original one, the (b) image offers in fact more visual information than image (d).



(a) The Original Image



(b) Bright-channel Enhanced Image



(c) Enhanced Image using both Channels



(d) Final Enhanced Image (Guided)

Figure A.4: Sample Results: walkway. Note how the patches on the columns are gradually resolved.



(a) The Original Image



(b) Bright-channel Enhanced Image



(c) Enhanced Image using both Channels



(d) Final Enhanced Image (Guided)

Figure A.5: Sample Results: garden (photo taken by me).

Appendix B

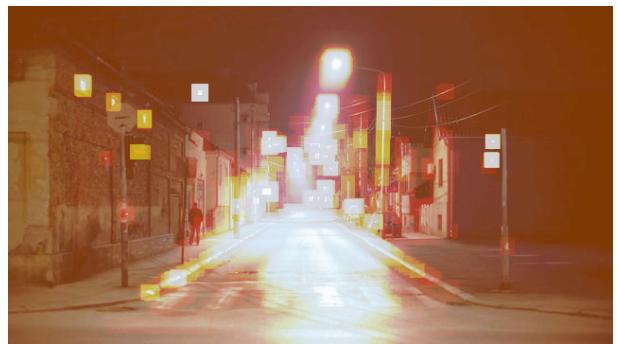
Bad Results

When the original image contained a larger bright patch (a big source of light, for example), the method failed to obtain good-quality results.

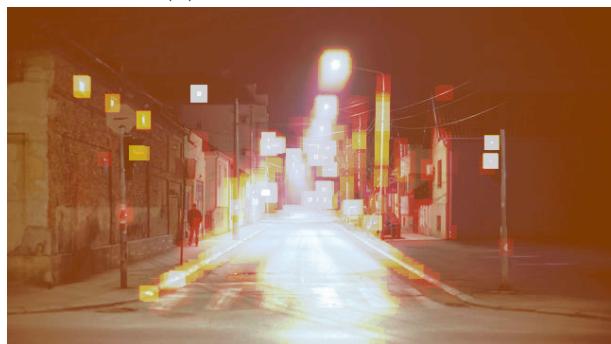




(a) The Original Image



(b) Bright-channel Enhanced Image



(c) Enhanced Image using both Channels

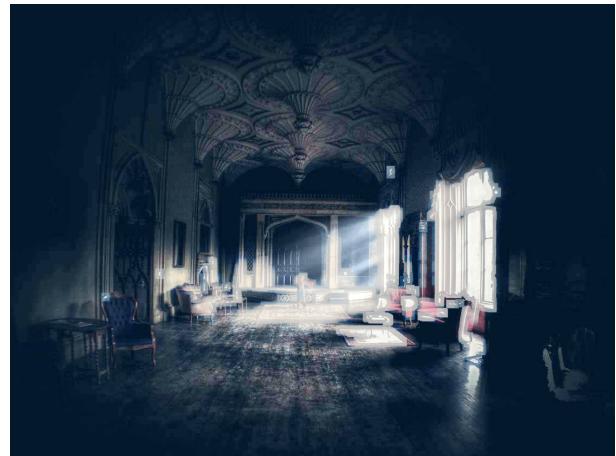


(d) Final Enhanced Image (Guided)

Figure B.1: Sample Results: street



(a) The Original Image



(b) Bright-channel Enhanced Image



(c) Enhanced Image using both Channels



(d) Final Enhanced Image (Guided)

Figure B.2: Sample Results: palace