Luminance Aware Color Transform For Multiple Exposure Correction Benchmark

Ahmet Kürşad Şaşmaz
Presentation Link : https://youtu.be/xJ9cLJQf160

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1 Introduction

1.1 Problem

The process addresses the conversion of underexposed or overexposed images into normally exposed images. Underexposure and overexposure are often the result of suboptimal camera settings or challenging working conditions during the image capture process. These non-ideal exposure levels can significantly degrade the quality of the captured images, rendering them less useful for subsequent analysis or applications. Correcting these exposure issues is crucial for ensuring that the images are suitable for further processing and analysis. This involves applying techniques from the fields of computer vision and deep learning to adjust the exposure levels, thereby restoring the images to their intended appearance with optimal brightness and contrast.

1.2 Previous Works

Previously proposed classical methods for exposure correction include histogram equalization algorithms such as Contrast Limited Adaptive Histogram Equalization (CLAHE) and gamma correction algorithms for perceptual exposure correction. These methods aim to adjust the image histogram to improve the visual quality and correct exposure levels. However, in addition to these traditional techniques, there are also deep learning-based solutions available. These deep learning approaches offer advanced capabilities by learning from large datasets to automatically correct exposure levels. Nonetheless, these solutions typically provide unidirectional exposure correction, either converting overexposed images to normally exposed ones or underexposed images to normally exposed ones. The challenge remains in developing more versatile models that can handle both types of exposure corrections efficiently and accurately.

1.3 Proposed Solution

The study presented in this paper aims to provide bidirectional exposure correction, addressing both overexposed to normally exposed and underexposed to normally exposed transformations. The proposed solution involves assessing the luminance features of the input image to determine whether it is too bright or too dark. Based on this assessment, multiple color transformations are then applied to the image channels to adjust the exposure to the desired level. This method allows for more flexible and accurate exposure correction, enhancing the overall quality and usability of the corrected images.

2 Data Collecting

2.1 Setup

For the creation of the dataset, a Canon R10 mirrorless camera equipped with a Canon 50mm prime lens was utilized. By employing the camera's HDR capability, sequential shots were taken at neutral exposure, positive exposure, and negative exposure settings. Subsequently, the HDR fusion algorithm embedded within the camera was used to generate HDR images. These HDR images were then employed as the ground truth for the study.

2.2 Collecting

A total of 292 captures in 73 scenes were made within the Middle East Technical University (METU) campus, utilizing scenes devoid of dynamic objects. To ensure that the dataset encompassed a broader dynamic range, the negative and positive exposures were set 3 exposure stops apart from the neutral exposure. To achieve more detailed results on edge cases, photographs were taken of scenes featuring a wide variety of lighting conditions within the frame.

2.3 Parsing

The captured photographs were converted to JPEG format and their file paths were recorded in a JSON file alongside the corresponding ground truth file paths. This was done to facilitate feeding the images into the experimental setup.

3 Methodology

3.1 Implementation

A script was developed to iterate through the dataset, run the comparison algorithms, merge and save the resulting image outputs, and record the calculated metrics for further analysis. This script facilitates the systematic evaluation of different algorithms by processing each image in the dataset, storing the results, and enabling detailed analysis based on the recorded metrics.

3.1.1 LACT

This class is designed to load the weights of the deep learning model that will be used for comparison and to perform inference when called. It serves as the structure for initializing the model with pre-trained weights and facilitates the generation of predictions on new data during the evaluation process.

3.1.2 CLAHE

This class initializes and applies the histogram equalization algorithm used for comparison. It provides the structure to initialize the algorithm and applies it when called, enabling the transformation of images through histogram equalization for comparative analysis.

3.1.3 Gamma Correction

This class initializes and applies the iterative gamma correction algorithm used for comparison. It provides the structure to initialize the algorithm and applies it when called, allowing for the adjustment of image exposures through iterative gamma correction for comparative analysis.

3.2 Metrics

3.2.1 PSNR

$$\text{PSNR(x,y)} = 20 \log_{10} \frac{255 * W * H}{\sum_{i=1}^{W} \sum_{j=1}^{H} (x[i,j] - y[i,j])^2} \tag{1}$$

3.2.2 SSIM

$$\text{SSIM(x,y)} = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{2}$$

3.3 Experimentation

All algorithms intended for comparison were executed across the entire dataset. The results were recorded and subsequently analyzed.

4 Results

4.1 Neutral Exposure Results

Algorithm	PSNR Avg	SSIM Avg
LACT	15.58	0.61
CLAHE	16.76	0.65
Gamma	**18.61**	**0.77**

Figure 1: Neutral Exposure Correction : Ground Truth, Image, LACT Prediction, CLAHE Applied Image, Gamma Correction Applied Image

4.2 Negative Exposure Results

Algorithm	PSNR Avg	SSIM Avg
LACT	12.61	0.39
CLAHE	13.55	0.45
Gamma	**17.92**	**0.54**

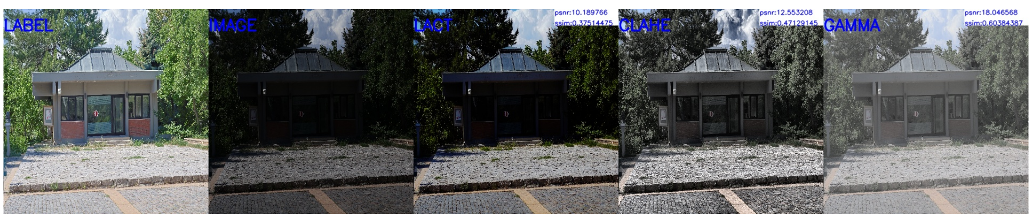

Figure 2: Negative Exposure Correction : Ground Truth, Image, LACT Prediction, CLAHE Applied Image, Gamma Correction Applied Image

4.3 Positive Exposure Results

Algorithm	PSNR Avg	SSIM Avg
LACT	**12.79**	**0.42**
CLAHE	9.86	0.35
Gamma	10.31	0.32

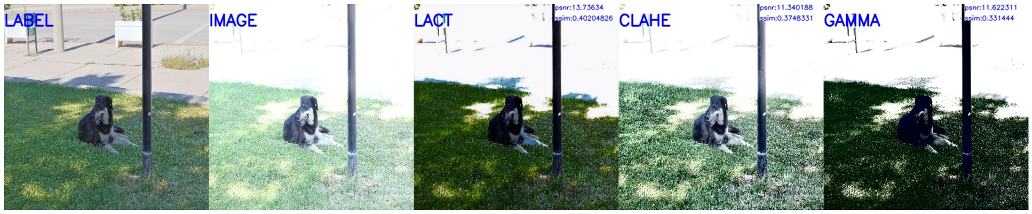

Figure 3: Positive Exposure Correction : Ground Truth, Image, LACT Prediction, CLAHE Applied Image, Gamma Correction Applied Image

4.4 HDR Results

Algorithm	PSNR Avg	SSIM Avg
LACT	17.93	0.83
CLAHE	16.20	0.71
Gamma	**29.50**	**0.93**

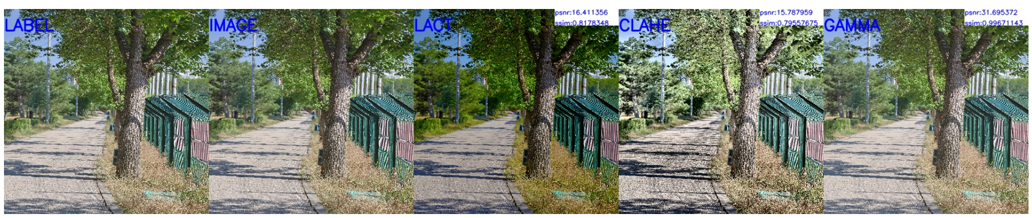

Figure 4: HDR Exposure Correction : Ground Truth, Image, LACT Prediction, CLAHE Applied Image, Gamma Correction Applied Image

4.5 All Results Without HDR

Algorithm	PSNR Avg	SSIM Avg
LACT	13.66	0.47
CLAHE	13.39	0.48
Gamma	**15.61**	**0.54**

4.6 All Results

Algorithm	PSNR Avg	SSIM Avg
LACT	14.73	0.56
CLAHE	14.09	0.54
Gamma	**19.09**	**0.64**

5 Discussion

As observed, the histogram equalization algorithm (CLAHE), one of the classical methods for exposure correction, never achieved the highest values when compared among the three methods evaluated.

Furthermore, the deep learning-based LACT model, expected to outperform classical methods, surpassed the other algorithms only in positive exposure values.

According to our analysis, both with and without the addition of ground truth data, the gamma correction algorithm consistently outperformed the other two methods. It optimizes gamma values iteratively based on average brightness, demonstrating superior performance.

In conclusion, based on the outputs from this dataset, an algorithm that performs mathematical operations directly on the image and iteratively optimizes gamma values using average brightness, rather than a deep learning-based approach like LACT, is expected to yield better results.

In addition to performance metrics, in terms of processing speed, the gamma correction algorithm, as a classical method, will provide better real-time performance in systems compared to the deep learning model LACT.

6 Conclusion

In this report, we compared the proposed method from the paper "Luminance Aware Color Transform For Multiple Exposure Correction" a deep learning solution for exposure correction, with traditional methods commonly used to address the same problem.

Upon benchmarking the proposed solution with a custom dataset, it was observed that the metrics provided in the paper were not consistently reflected in our evaluation. One of the classical methods consistently outperformed the proposed deep learning approach in overall performance.