Adaptive Gamma and Contrast Correction(AGCC) for enhancing images in low light

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Abstract

Enhancing images captured under low-light conditions is a significant challenge in computer vision. Poor illumination often degrades image quality, leading to low contrast, high levels of noise, and blurred details. This paper proposes a novel low-light image enhancement method called Adaptive Gamma and Contrast Correction (AGCC). The model analyzes the brightness of the input image and calculates the average color values to determine adaptive gamma and contrast coefficients. These values are computed automatically and adjusted dynamically based on varying illumination levels, eliminating the need for manual tuning. Both qualitative and quantitative evaluations demonstrate that the AGCC model effectively enhances low-light images while preserving fine details, maintaining natural contrast, and ensuring accurate color representation. The resulting images exhibit visually pleasing and natural appearances. Due to its efficiency and robustness, AGCC can offer a practical solution for various applications, including night-time surveillance, medical image enhancement, and photography in low-light environments.

Keywords — Low light image enhancement, evaluation metrics, low light datasets

1 Introduction

Low light is a major challenge in computer vision[1]. It reduces the scene's image quality regarding contrast and detail clarity [2]. Imperfect lighting increases noise and loss of detail in dark areas [3]. Low-light image enhancement plays an important role in human life because it enters into many fields, the most important of which are the military [4], security, health, night photography [5], and smart driving fields [6]. Low-light image enhancement techniques aim to restore lost information and enhance lighting without overdoing it, in addition to achieving a balance between removing noise, enhancing contrast, restoring details, and improving colors so that images are closer to natural images [7]. An approach proposed in this paper uses adaptive gamma and contrast correction (AGCC), a technique based on dynamically adjusting the illumination distribution within an image based on local analysis of brightness levels [8]. Details in low-light areas are improved without distortion or loss of information in Bright areas. It allows visual improvements to images without brightening bright parts or amplifying noise in dark areas [9].

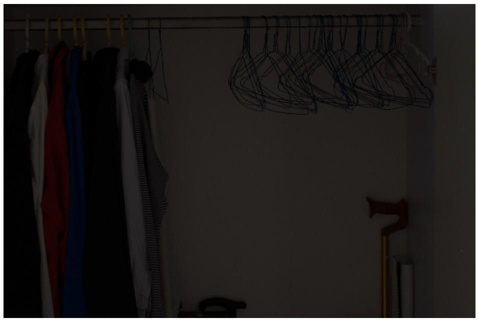
Fig. 1 illustrates the intensity distribution of a low-light image and the corresponding enhanced result produced by the proposed Adaptive Gamma and Contrast Correction (AGCC) method.

The main contributions of the proposed model are summarized as follows:

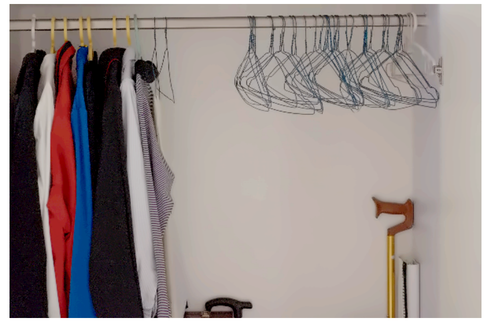
1. Improved computational efficiency – The method increases processing speed and reduces computational complexity, making it suitable for real-time or resource-constrained applications.

2. Effective brightness enhancement – the model enhances image brightness to closely resemble that of normally illuminated scenes, while simultaneously suppressing noise for improved visual quality.

3. Adaptive parameter selection – The model autonomously selects appropriate baseline parameters for processing, ensuring robustness across a variety of low-light scenarios without the need for manual adjustment.



(a) Low-light image



(b) Enhanced image

Figure 1: Illustrates the intensity distribution of a low-light image and the corresponding enhanced result produced by the proposed Adaptive Gamma and Contrast Correction (AGCC) method.

2 The proposed model adaptive gamma and contrast correction (AGCC)

The proposed model, Adaptive Gamma and Contrast Correction (AGCC), is designed to enhance low-light images through a series of adaptive, data-driven steps. The enhancement process consists of the following main stages:

1. Brightness and color analysis: The model first analyzes the input image by computing its overall brightness factor along with the average RGB values. This step provides a global understanding of the illumination and color distribution, which guides subsequent adjustments.

2. Noise estimation and reduction: A noise suppression coefficient is then estimated based on the brightness and color characteristics of the image. This coefficient is used to perform targeted denoising, effectively reducing the noise commonly present in low-light conditions without over-smoothing important details.

3. Adaptive gamma correction: Next, an adaptive gamma value is calculated to correct the image's tonal range. This gamma coefficient is dynamically adjusted according to the illumination level, allowing the model to brighten dark regions while preserving natural brightness transitions.

4. Contrast enhancement: Finally, a contrast enhancement factor is computed and applied to improve the visual distinction between light and dark regions. This step sharpens the image structure and restores detail, further improving visibility and perceptual quality. Through these steps, AGCC provides a robust and fully automatic enhancement pipeline that adapts to varying lighting conditions without manual intervention, making it suitable for practical low-light image enhancement tasks.

The source code is publicly available at:
`https://github.com/FakedSky122/Adaptive-Gamma-and-Contrast-Correction`.

A. Luminance factor (L)

The luminance factor can measure the average distribution of brightness in an image. It uses red, green and blue channel(r, g, b) to calculate, and based on the sensitivity of the human eye.

$$L = 0.2126r + 0.7152g + 0.0722b$$

Where r, g, b refers to the mean's channels of red, green, and blue.

B. Color mean factor (C)

The average color factor is the sum of the average values of each channel red, green and blue(r, g, b).

$$C = (r + g + b) \div 3$$

Where r, g, b are the mean values of the red, green, and blue channels.

C. Adaptive gamma coefficient (γ)

The adaptive gamma coefficient is calculated for the image, it is based on the luminance factor(L) and the color mean factor (C)

$$\gamma = 500 \div \sigma \times (L \div C)$$

Where σ is the standard deviation of the gray scale of the input image, it is the control parameter in this model. Here $500 \div \sigma$ must less than 25.

D. Appling adaptive gamma correction

The adaptive gamma coefficient is calculated for the image, it is based on the luminance factor(L) and the color mean factor (C)

$$I_o = (I_i)^{2 \div \gamma}$$

Where I_o refers to the output image, I_i refers to the input image.

E. Calculate and apply adaptive contrast correction

The adaptive contrast coefficient (F) is calculated for the image, it is based on the luminance factor(L) and the gamma coefficient (γ). Then the model will use contrast stretching to enhance the image.

$$F = (50 \div \sigma + \gamma \div 5) \div 1.5$$

Where σ is the standard deviation of the gray scale of the output image.

3 Result discussion

To evaluate the performance of the proposed model, it is tested on the LOL dataset. The results were compared with 3 algorithms at the leading level: IAGC [10], LGMS [11], and LIEW [12].

Algorithm (on LOL dataset)	PSNR↑	SSIM↑
IAGC[10]	11.260	0.468
LIEW[12]	12.678	0.638
LGMS[11]	15.834	0.475
AGCC	18.343	0.899

Table 1: Compare the model's (AGCC) results with the set of algorithms on LOL dataset, using PSNR and SSIM metrics.

(a) Comparison

Figure 2: Comparison of AGCC and other models on LOL dataset.

The images are evaluated visually, as shown in Figures 2. It was observed that the proposed model (AGCC) produced enhanced images with balanced brightness and high contrast while maintaining fine details as well as low noise levels.

4 In conclusion

Quantitative evaluations on benchmark datasets demonstrate that AGCC outperforms representative state-of-the-art methods in both PSNR and SSIM, while qualitative assessments confirm its ability to produce natural-looking images with accurate color reproduction.

Owing to its low computational cost and training-free nature, AGCC is well-suited for deployment in resource-constrained platforms such as embedded vision systems, mobile photography, and real-time video surveillance.

In conclusion, experimental evaluations demonstrate that AGCC achieves consistently favorable results in both visual quality and computational efficiency.

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