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Comparison and Evaluation of Low-light Image Enhancement Methods

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Abstract: Low-light images generated under insufficient illumination, including low brightness, color distortion, noise amplification, and loss of detail information. This issue degrades visual perception quality significantly and restricts the performance of high-level computer vision tasks severely such as object detection, image segmentation. Low-light image enhancement aims to recover visually friendly, high-quality images from degraded low-light inputs while preserving texture details and correcting color deviation. This paper presents a low-light image enhancement methods survey, systematically reviewing traditional model-based approaches, analyzing the peak signal to noise ratio (PSNR) characteristics and elaborating their core principles, advantages, and limitations. Current research challenges and future trends were discussed, including real-time processing, extreme low-light restoration and multimodal fusion enhancement. This survey aims to provide a systematic reference for researchers in the fields of image processing, computational photography, and computer vision.
Keywords: low-light image; image enhancement; image restoration; computer vision

1. Introduction

With the rapid development of digital imaging devices, image acquisition and analysis systems have been widely applied in security monitoring, autonomous driving, medical imaging, remote sensing detection, mobile photography, other daily life and industrial fields [1]. In practical application scenarios, imaging equipment is often affected by insufficient environmental light, backlight, uneven illumination, short exposure time, and sensor limitations, resulting in low-light images with obvious quality degradation [2]. These degraded images exhibit the following typical characteristics: extremely low overall brightness, compressed dynamic range, blurred edge details, severe noise interference and/or low signal-to-noise ratio [3]. Such quality degradation not only reduces the subjective visual experience of human observers but also leads to a sharp decline in the accuracy and robustness of high-level computer vision algorithms, limiting the performance and application scope of intelligent vision systems.

Low-light image enhancement is a core preprocessing task in the field of image processing and low-level vision [4]. Its goal is to improve the brightness and contrast of low-light degraded images, suppress noise, correct color deviation, restore lost detail information, and output clear, natural, and high-quality enhanced images[5]. Effective low-light image enhancement technology can significantly improve the visual quality of images, provide reliable data support for subsequent high-level vision tasks, and expand the application scenarios of imaging systems in extreme lighting conditions. Therefore, the researches on efficient and robust low-light image enhancement methods have important theoretical value and practical application significance [6,7, 8].

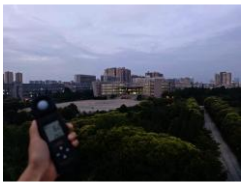
The degradation mechanism of low-light images is complex and diverse, mainly affected by environmental lighting, imaging hardware, and signal transmission processes [9]. The core degradation characteristics are (1) Insufficient incident light leads to low pixel intensity values, and the effective dynamic range of the image is seriously compressed, resulting in most pixel values being concentrated in the low-gray area, with obvious underexposure; (2) Low illumination leads to weak contrast between image regions, and subtle texture and edge details are submerged in the dark background, resulting in blurred content and difficult recognition; (3) The imaging sensor has low sensitivity in low-light environments, and the readout noise, thermal noise, and quantization noise are significantly amplified during signal amplification, showing obvious graininess, color spots, and block artifacts, and in real scenes, the illumination distribution is often uneven, with local dark areas and local bright areas coexisting, increasing the difficulty of adaptive enhancement [10].

The research of low-light image enhancement has gone through the development stage from traditional model-driven methods to modern data-driven deep learning methods [11]. Traditional methods rely on manually designed image priors, mathematical models [12], and heuristic rules to achieve enhancement, including spatial domain transformation (histogram equalization, gamma correction), frequency domain filtering, and Retinex theory-based decomposition methods. These methods have clear interpretability but limited performance in complex real low-light scenes. Deep learning methods uses large-scale paired or unpaired datasets to train deep neural networks, automatically learn the mapping relationship from low-light images to normal-light images, and achieve end-to-end enhancement. These methods have strong feature extraction and representation capabilities, showing superior performance in complex degradation scenarios, and have become the mainstream research direction in this field [13]. Previous traditional low-light image enhancement methods rely on manually designed mathematical models and image processing priors, without addressing on the low level of images. Therefore, this paper studies the effectiveness of low-light image enhancement including gamma correction, histogram equalization and contrast stretching, etc.

2. Experimental Design and Data Analysis

In computer vision and image processing, captured images often suffer from insufficient contrast caused by uneven or inappropriate lighting. Low illumination reduces visibility of texture and edge details; overly strong illumination leads to washed-out regions. Both degrade the performance of subsequent tasks such as object detection, feature extraction, and image measurement.

Table 1: Comparison for enhancement methods of different illuminance-level images

Illumin-ance level (Lux)	*Original image*	*Gamma Correction (1.5)*	*Contrast Stretching [0.3 0.7]*	*Histogram Equalization*
2				
62				
272				
2134				

Further, image quality degrades significantly under non-uniform or extreme illumination, leading to low contrast, blurred details, and unreliable visual analysis. In this study, we acquired images at calibrated illuminance levels with a professional illuminance meter (Xima Digital Lux METER AS803 smart sensor, Measurement range: 0 - 200000 Lux, Producted by Dongguan WanChuang Electronic Products Co., Ltd.) to ensure accurate lighting control. We then evaluate classic spatial-domain enhancement techniques: Gamma Correction (GC), Contrast Stretching (CS) and Histogram Equalization (HE). PSNR Value is used to compare different (low, medium, and high illumination) images. Comparison for enhancement methods of different illuminance-level images are shown in the Table.1, and the PSNR values for comparison of enhancement methods are shown in the Table.2.

Results show that Gamma Correction provides stable, natural enhancement at extremely low-light illuminance 2 Lux, while the Gamma Correction provides more stable natural enhancement at the low-light illuminance 62 Lux. Histogram Equalization delivers stronger contrast boost and recovers more details in dark regions but tends to amplify noise and cause over-enhancement under low light. Contrast Stretching is relatively common among these methods.

Table 2: PSNR value comparison for enhancement methods

Illuminance-level(Lux)	Gamma Correction (1.5)	Contrast Stretching [0.3 0.7]	Histogram Equalization
2	7.4299	7.4392	7.4410
62	5.0384	5.0475	5.0437
272	4.7005	4.7095	4.7053
2134	4.2827	4.2925	4.2872

Gamma correction is a classic nonlinear intensity transformation method, which adjusts the mapping relationship between the input pixel value and the output pixel value through a power function to correct the brightness of the image. Histogram Equalization improves the image contrast by stretching the gray histogram of the image to the full dynamic range. The core idea is to map the original concentrated gray distribution to a uniform distribution through a cumulative distribution function, expand the gray level interval, and enhance the contrast between different regions. Histogram Equalization can effectively improve the global contrast of the image, but it ignores the local detail information, is prone to over-enhancement, noise amplification, and color distortion, and has poor effect in uneven illumination scenes.

3. Conclusions

Histogram Equalization uses the cumulative distribution function to redistribute pixel values toward a uniform histogram. It significantly expands contrast but may over-amplify flat regions and noise, especially in dark images.Many improved variants have been proposed to reduce artifacts. However, basic CS and HE remain dominant in real-time and resource-constrained systems. A controlled comparison under calibrated illuminance is still missing. Image enhancement aims to improve visual quality by adjusting pixel intensity distribution. Among traditional methods, Gamma Correction, Contrast Stretching and Histogram Equalization are widely used due to simplicity and efficiency. However, their performance varies drastically under different lighting. Most existing comparisons lack strictly controlled illuminance data. To address this, we use an illuminance meter to record accurate Lux values and capture image sets under stable, graded lighting conditions. We then compare the methods systematically. Results show that Histogram Equalization delivers stronger contrast boost and recovers more details in dark regions but tends to amplify noise and cause over-enhancement under low light. This work provides a practical reference for selecting image enhancement strategies under measured lighting conditions.

Low-light image enhancement is a key research topic in the fields of image processing and computer vision, which is of great significance for improving image visual quality and the performance of high-level vision tasks. With the continuous innovation of deep learning technology and the continuous expansion of application scenarios, low-light image enhancement methods will be more efficient, robust, and intelligent, providing strong support for the development of intelligent vision systems in low-light environments.

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