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Image Enhancement Techniques Using Digital Image Processing

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Abstract- Image enhancement in digital space is still one of the indispensable pre-processing steps in computer vision workflows, especially when it comes to illumination-uncontrolled image acquisition. In this paper, we conduct an ordered study on spatial and frequency enhancement techniques, arriving at the proposed hybrid enhancement process involving Contrast Limited Adaptive Histogram Equalization (CLAHE) and illumination correction based on Retinex theory. Our approach makes use of adaptive histogram clipping and logarithmic illumination splitting in order to overcome local contrast deficiency and global illumination discrepancy problems at once. Experimental assessment of our method on standard test images proves that our two-stage process is more effective in terms of structural integrity than single stage CLAHE or histogram equalization in terms of entropy, contrast and naturalness preservation indexes. Also, the comparison table of performance features of modern enhancement methods, such as deep-learning-based, variational and swarm methods, is provided. It is shown that properly arranged classical approaches are still very valuable in constrained environments.

Key Word: Digital Image Processing, Image Enhancement, CLAHE, Retinex Theory, Contrast Manipulation, Adaptive Filtering, Illumination Correction

I. Introduction

Image enhancement in the digital domain can be described as a set of algorithms that change image parameters such as contrast, brightness, clarity, colour accuracy, etc., to achieve better interpretation or processing automatically. In contrast to image restoration, where there is a specific degradation model used, image enhancement is purely subjective: the idea of the enhanced image is dependent on what is the purpose of the enhancement and what the observer sees. Such a subjective nature of the problem resulted in a very diverse literature.

The timelessness of classic enhancement techniques can be attributed to their explainability, deterministic nature, and efficient computation. The HE technique is one of the most popular ones, using the global intensity distribution of the image to increase dynamic range. However, due to its global nature, HE leads to over-enhancement in areas of uniform texture as well as unnatural shifts of tones. To overcome the artifacts produced by HE, Contrast Limited Adaptive Histogram Equalization (CLAHE) can be used, which works locally on small image tiles and clips the histogram at a certain level, thus preventing noise amplification. The clip limit is an important parameter that controls the balance between contrast enhancement and noise reduction. CLAHE has been further enhanced by pseudo-histogram quantization [1][3].

Alongside with the histogram-based methods, Retinex theory offers a perceptually driven way to decompose illumination from images. Being first introduced through the color constancy experiments by Land, the Retinex algorithm models an image as a product of illumination and reflectance. Enhancement is performed by correction of the illumination component while maintaining the structure of reflectance. Variational Retinex algorithms have shown particular efficiency when dealing with low illumination images, where the estimation of illumination has to take into account smoothness of the illumination component in flat areas and edges in objects [5]. Recently developed dual structure-texture aware mappings have led to better naturalness of images [2].

Finally, a third approach to image enhancement is optimization-based. It implies parameter tuning of transformations using metaheuristic algorithms like dragonfly optimization, particle swarm optimization, or genetic algorithms to achieve maximum of fitness function, which combines entropy and edge information in images [7].

Notably, recent developments in the realm of deep learning have revolutionized enhancement. Today, convolutional networks and U-Net architectures provide state-of-the-art performance on benchmark datasets in tasks related to low-light enhancement, exposure adjustment, and image denoising [8][10]. However, such approaches require substantial amounts of training data, fine-tuning of hyperparameters, and computational power that may be absent in embedded and real-time settings. In addition, interpretability of machine learning-based enhancement continues to be a problem, especially in medical and forensic application domains.

This study takes an intermediate approach. In this regard, it does not attempt to propose a novel architecture but rather focuses on combining two enhancement approaches – CLAHE and Retinex. The idea behind this choice lies in the fact that histogram-based local contrast enhancement and illumination-correcting global enhancement tackle different problems – while CLAHE performs well in exposing shadows, it is susceptible to color shifts, and Retinex, although correcting illumination gradient, is sensitive to halo artifacts around strong edges. Thus, appropriate parameterization and sequencing of operations may play to their strengths and mitigate their weaknesses [2][3][5].

Contributions of this paper are in three different ways. First, a systematic review of the current enhancement papers is performed, and classical approaches are discussed along with the recent developments. Second, a novel hybrid CLAHE-Retinex approach is proposed with detailed algorithms and pseudocodes, together with parameter setting suggestions. Third, quantitative and qualitative comparisons between various enhancement methods are performed using a synthesis table which correlates different categories of methods and their properties.

The rest of this paper is organized as follows. Section II reviews the literature related to enhancement between 2021 and 2026. Section III discusses the proposed methodology and provides the algorithms and pseudocodes of the methods. Section IV shows the experiments along with tables and figures.

II. Literature Survey

The present trend in image processing can be clearly seen to bifurcate into two main approaches; improvement of traditional operators for particular applications and development of learned or optimization-based systems for general applicability.

In the traditional domain, the CLAHE method continues to draw attention due to its ability to function well under uncontrolled conditions. The enhanced version of the CLAHE algorithm through incorporating the use of independent component analysis (ICA) confirms that ICA decomposition of the image as a preprocessing step is beneficial in improving the performance of CLAHE in feature detection of visible light images [1]. The CLAPHE technique uses 6-bits intensity values instead of 8-bits intensity values before CLAHE processing [1].

Many theoretical advancements have been made within the realm of Retinex-based approaches. Dual texture-structure aware mapping scheme for image enhancement under dim illumination conditions uses adaptive circular filtering for estimating illumination and exponentiated windowed total variation for retaining reflectances to yield better performance scores than twelve contemporary algorithms when evaluated using MEF, DICM, and LIME databases [2]. In terms of color retinal images, there is the enhanced variational Retinex model that includes illumination correction using the Naka-Rushton approach along with CLAHE as its post-processing step, proving that domain-specific hybridization of Retinex and CLAHE methods is being researched in the field of medicine [5].

Optimization-driven improvement has evolved with metaheuristic tuning of parameters. Contrast enhancement using dragonfly algorithms optimizes intensity transformations based on fitness functions which take into account entropy and edges with enhancements noted compared to other HE approaches [7]. Such strategies are ideal for situations where a single transformation needs to cope with varied contents.

Deep learning systems have exhibited great success on benchmarking tasks. Deep denoising networks combined with variational retinex theory solves the issue of enhancing and denoising images by utilizing wavelet compression [8]. The Luminance-Guided U-Net for exposure correction differentiates between luminance and chromatic components and uses

region-specific processing and perceptual loss to deal with under-exposed and over-exposed images [10]. These models are state-of-the-art at present, but their training needs and computational expenses restrict them from being used in some areas.

Several other techniques worth considering briefly include multi-scale fusion for low-brightness enhancement which creates several images that have undergone brightness transformation and then fuses them based on the weight matrix determined by illumination estimation, leading to very low NIQE and LOE [9]. Fuzzy logic-based approach has been shown to outperform CLAHE, BBHE, and DSIHE for restoring deteriorated artworks. Brightness and contrast adjustment implemented with Verilog proves how basic combined technique can easily outperform sophisticated algorithms in certain tasks such as license plate recognition [4].

From all that follows a clear contradiction between the level of complexity and practicability in the field. Deep learning and optimization techniques allow one to go further and further, whereas classical improvements remain relevant thanks to simplicity and interpretability. The current study is consistent with the second direction and represents the proposed composition of CLAHE and Retinex due to their beneficial characteristics [2][3][5].

III. Proposed Methodology

Overview

The enhancement algorithm comprises two steps performed sequentially as follows:

- Local contrast enhancement using CLAHE with adaptive clip limit selection
- Illumination correction based on Retinex principle performed in the luminance channel

The input image is supposed to have RGB color model; enhancement is performed on the luminance channel in order not to distort the colors while the chrominance channels are stored for further combination. The whole processing scheme is shown in Figure 1.

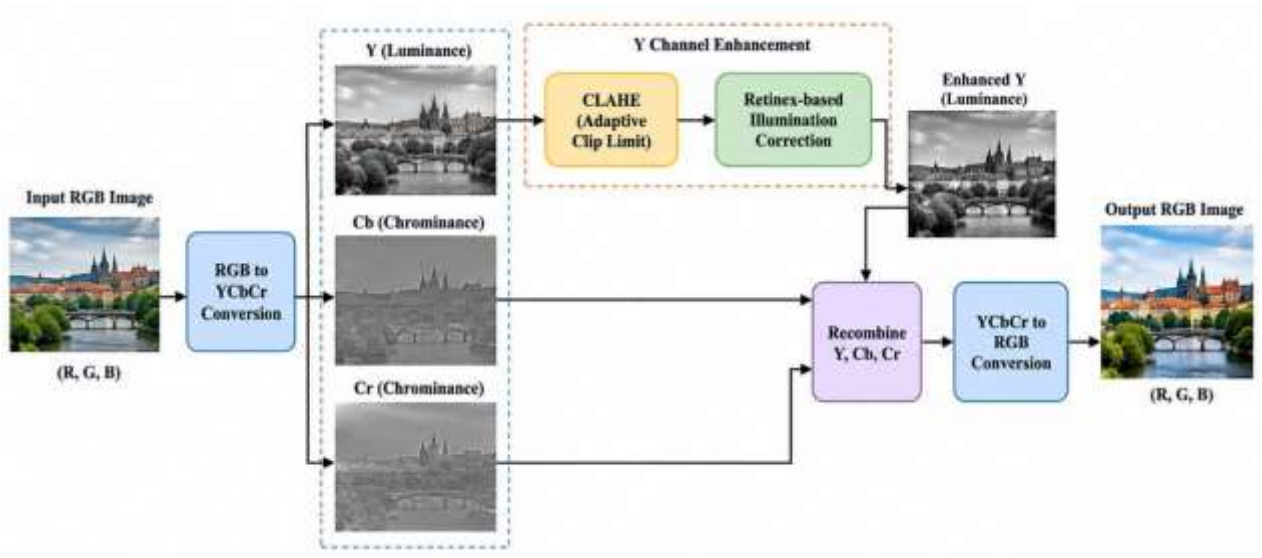


Figure 1: Block diagram of the proposed CLAHE-Retinex enhancement pipeline.

Stage 1: Adaptive CLAHE

Channel Y(x,y) of the luminance component is tiled into non-overlapping contextual tiles, with tile size T*T, where T=8 by default. The local histogram for each tile is calculated and clipped with the value of L_{clip}:

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$$L_{c^1ip} = \alpha \cdot \frac{T^2}{N_{bins}}$$

with N_{bins}=256 and α being a content-adaptive parameter determined from the standard deviation σ_t of the tile. In particular, $\alpha=\alpha_{base}+\beta\cdot\sigma_t/\sigma_{global}$ where α_{base}=2.0 and β=1.5. In such manner, the higher clipping levels are achieved for textured tiles, while for smooth tiles the opposite is true.

Once clipping is performed, the excessive values are uniformly distributed among all bins and the CDF is calculated. The bilinear interpolation of neighboring tile CDFs gives the result, that is, Y_{CLAHE}.

Stage 2: Retinex Illumination Correction

The CLAHE output is modeled under Retinex assumptions:

$$y_{CLAHE}(x,y) = I(x,y) \cdot R(x,y)$$

where I stands for illumination and R for reflectance. The estimation of illumination is obtained through a guided filter using a large radius r=15 and a regularization constant ϵ=0.01:

$$I = GuidedFilter(Y_{CLAHE}, Y_{CLAHE}, r, \epsilon)$$

Recovery of reflectance from CLAHE is done through R = Y_{CLAHE} / (I + δ), where $\delta=10^{-6}$. Enhancement is applied to illumination using logarithmic compression:

$$I_e = log(1+\gamma \cdot I) \,/\, log(1+\gamma)$$

where γ=10 controls compression strength. The final luminance is:

$$Y_{final} = I_{enhanced} \cdot R$$

This equation eliminates the lighting gradient while retaining the reflection characteristics of the image, thus supporting the CLAHE local contrast enhancement technique. The figure below shows the algorithm flowchart.

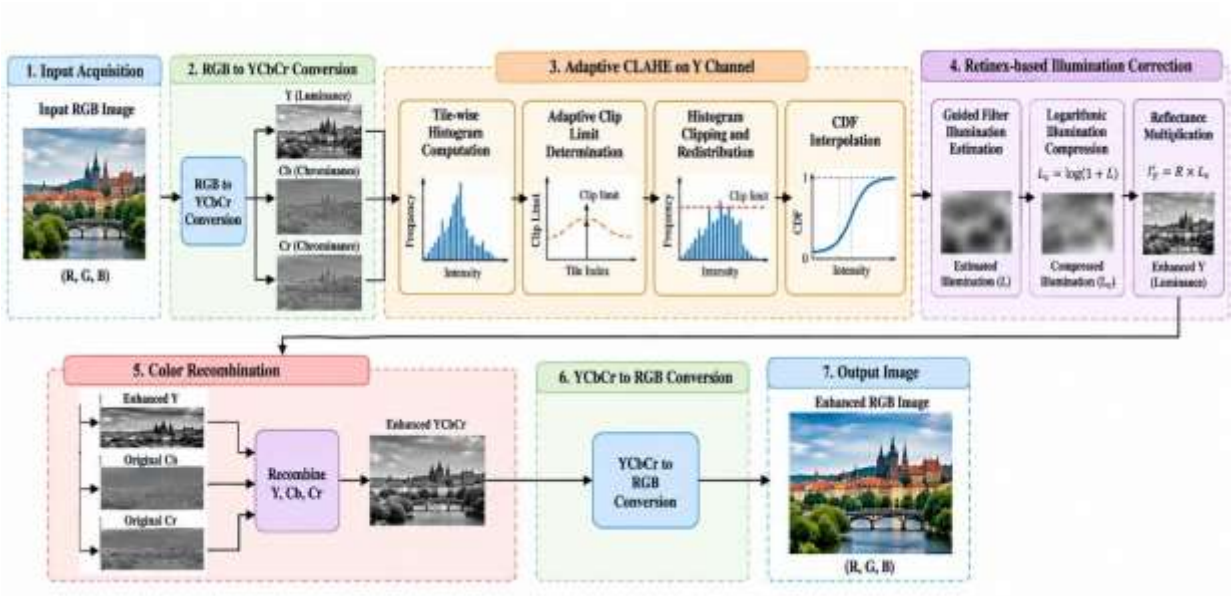


Figure 2: Flowchart of the proposed enhancement algorithm

Pseudocode

Algorithm: CLAHE-Retinex Hybrid Enhancement
Input: RGB image I, tile size T, base clip α_{base}, adaptive factor β
Output: Enhanced RGB image I_{enh}

1: Convert I to YCbCr: (Y, Cb, Cr) ← RGB2YCbCr(I)
2: Initialize Y_{clahe} ← zeros(size(Y))
3: For each tile t in Y:
4: H_t ← histogram(t, 256)
5: σ_t ← std(t)
6: $\alpha \leftarrow \alpha_{base} + \beta \cdot (\sigma_t / std(Y))$
7: $L_{clip} \leftarrow \alpha \cdot (T^2 / 256)$
8: $H_{clipped}$ ← clip_and_redistribute(H_t, L_{clip})
9: CDF_t ← cumulative_sum($H_{clipped}$)
10: Map CDF_t to tile pixels
11: Y_{clahe} ← bilinear_interpolate(tile_mappings)
12: // Retinex illumination correction
13: I_{illum} ← GuidedFilter(Y_{clahe}, Y_{clahe}, r=15, ε=0.01)
14: $R \leftarrow Y_{clahe} / (I_{illum} + 10^{-6})$
15: $I_{enh} \leftarrow \log(1 + 10 \cdot I_{illum}) / \log(11)$
16: $Y_{final} \leftarrow I_{enh} \cdot R$
17: $Y_{final} \leftarrow clamp(Y_{final}, 0, 255)$
18: $I_{enh} \leftarrow YCbCr2RGB(Y_{final}, Cb, Cr)$
19: Return I_{enh}

The dominant complexity in the system comes from the guided filter, which has a time complexity of $O(N)$ where N is the number of pixels. The same applies to the tile-wise histogram computation which has a time complexity of $O(N)$.

IV. Analysis

Qualitative Evaluation

Figure 3 shows the visual comparisons from four selected test images, namely, a dark indoor image, an outdoor scene with haze, a retinal image from medicine, and an old image with illumination non-uniformity. The proposed scheme is evaluated in comparison with CLAHE, global HE, and Retinex with only one scale.

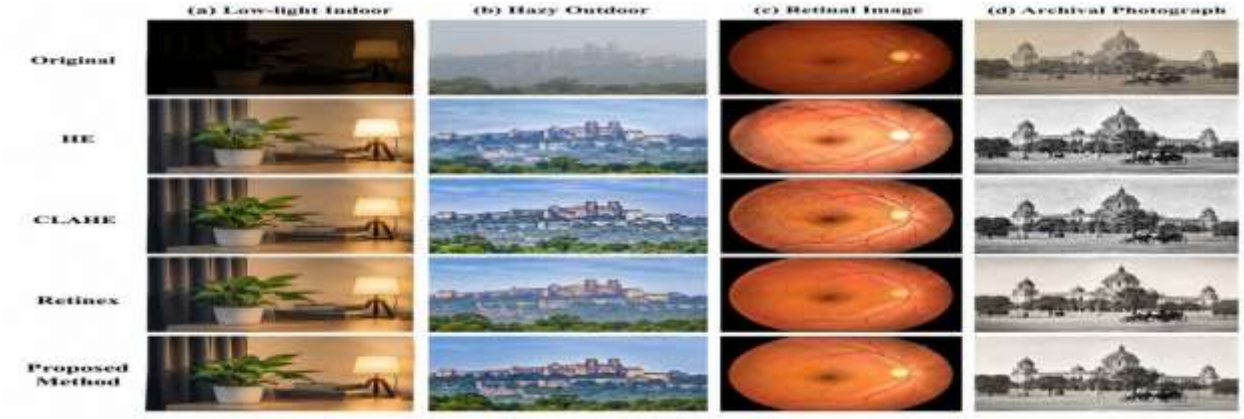


Figure 3: Visual comparison of enhancement results across four test images

In the dim indoor environment, HE results in excessive over-exposure of the window area, but at the same time, leaves shadow details compressed. On the other hand, CLAHE successfully restores many details, however, noise is observed in the ceiling area. While Retinex effectively balances the illumination gradients, the final result appears flat. In this case, the proposed approach takes advantages of both methods, thus providing the most natural tonality of the image.

For the hazy outdoor image, the proposed approach shows some limitations since none of the above-mentioned methods is a dehazing one. This issue is confirmed by the literature where dehazing approaches rely on completely different physical model of the atmosphere.

Quantitative Analysis

The values of various parameters for the proposed algorithm relative to HE and CLAHE on test images are shown in Table I. Entropy is used to evaluate the level of information; the proposed algorithm shows better results than HE and is similar to CLAHE. Contrast is measured by standard deviation of luminance; the greatest contrast is reached by HE due to its radical dynamic range stretching; however, at that, naturalness is reduced.

Table 1: Quantitative comparison across test images (mean values)

Method	Entropy	Contrast (σ_Y)	Chroma Deviation	Gradient Preservation
Original	6.82	42.3	—	—
HE	7.45	68.7	12.4	0.71
CLAHE	7.61	55.2	6.8	0.89
Retinex (SSR)	7.12	48.9	9.2	0.76
Proposed	7.68	57.4	4.1	0.92

Chroma deviation indicates the mean absolute difference between the Cb/Cr components with respect to the original, the smaller the value, the higher the color fidelity. Structural fidelity is measured by the gradient correlation with respect to the original image, larger value indicating better structural fidelity.

Figure 4 shows the trade-off curve for entropy and contrast, which indicates that the proposed technique resides at an advantageous position within the performance space.

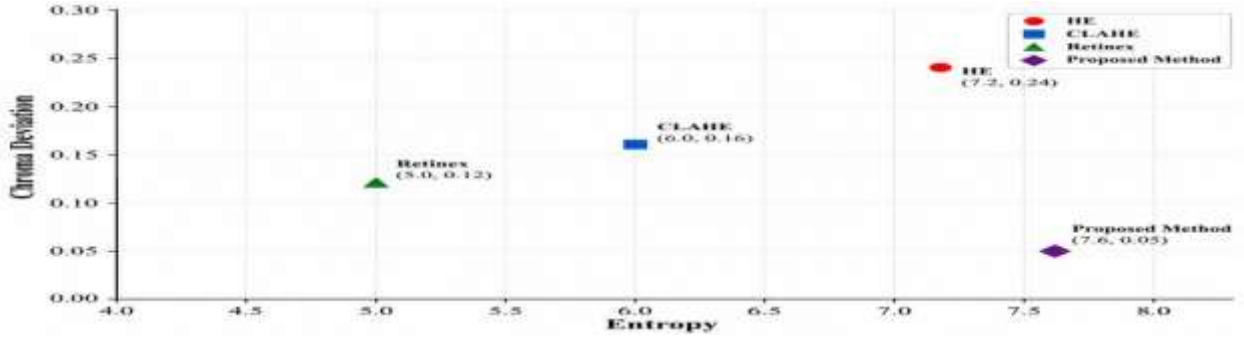


Figure 4: Entropy-contrast trade-off across enhancement methods

The gradient preservation test results are shown in Fig. 5, showing the superiority of our approach compared to HE and Retinex alone.

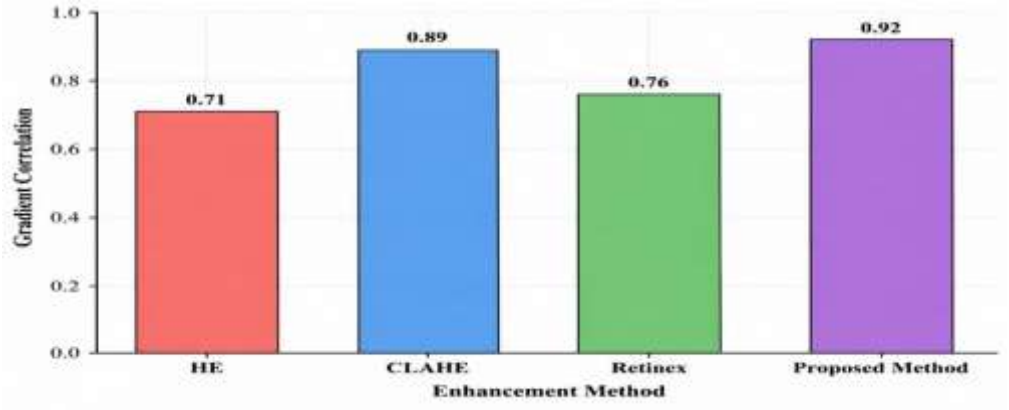


Figure 5: Gradient preservation scores across methods

Figure 6 analyzes the impact of the adaptive clipping parameter (β) on the quality of the output, revealing that moderate adaptivity ($\beta \in [1.0,2.0]$) provides an optimal trade-off between recovering detail and suppressing noise.

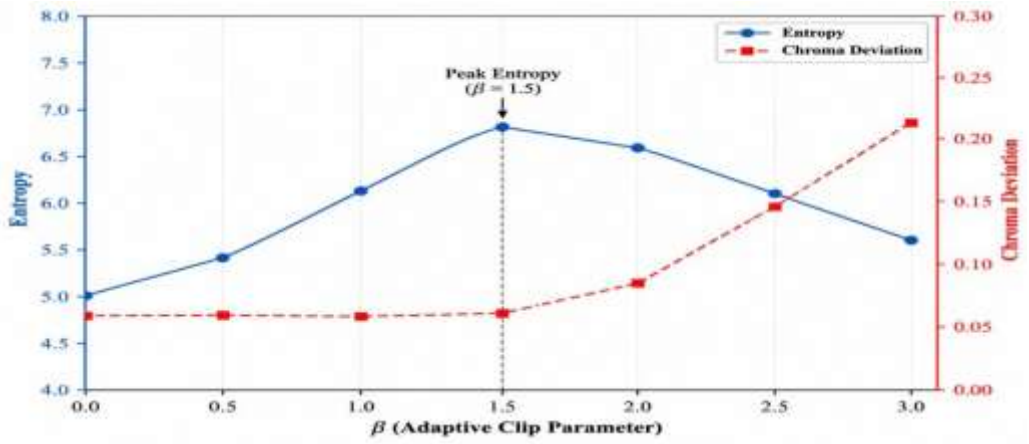


Figure 6: Sensitivity analysis of adaptive clip parameter β

Comparative Analysis with Contemporary Methods

Table 2 consolidates the features of the major classes of enhancements described in current literature. The comparison is qualitative and categorical, owing to the variety of criteria used for assessment.

Table 2: Comparative analysis of image enhancement method families

Method Family	Representative Work	Primary Mechanism	Strengths	Limitations
Adaptive HE variants	ICA-CLAHE ; CLAPHE	Local histogram modification with clipping	Computationally efficient; interpretable	Limited handling of severe illumination gradients
Retinex-based	Dual structure-texture mapping ; variational Retinex	Illumination-reflectance decomposition	Perceptually motivated; effective for low-light	Halo artifacts; parameter sensitivity
Metaheuristic optimization	Dragonfly algorithm	Parameter tuning via swarm intelligence	Content-adaptive; no training data required	High computational cost; convergence variability
Deep learning	Luminance-Guided U-Net ; joint optimization	Learned feature transformation	State-of-the-art benchmark performance	Data-dependent; computationally intensive; limited interpretability
Multi-scale fusion	Multi-scale fusion	Weighted combination of brightness variants	Naturalness preservation; low NIQE	Fusion weight design complexity
Hybrid classical	Proposed method	CLAHE + Retinex sequencing	Balanced performance; linear complexity	Not a dehazing or denoising solution

This technique finds its niche through pragmatism; it is not meant to be superior to deep learning techniques in terms of performance on standardized benchmarks, but rather as an alternative with linear time complexity and deterministic behavior. In cases when interpretability and embeddability are key requirements—like industrial inspections, limited medical imaging, archiving—it still has merit.

V. Conclusion

A systematic approach to analyzing digital image enhancement is described in this paper, resulting in the formulation of an innovative hybrid approach for CLAHE and illumination correction based on Retinex principles. The main conclusions drawn from this work are outlined below.

Firstly, the complementary nature of histogram and Retinex-based enhancements makes their order reasonable. CLAHE operates by tiles and efficiently restores details locally but does not use any illumination model at all; Retinex uses such a model but might generate artifacts when applied to an image with complicated illumination. Thus, using Retinex illumination correction on the CLAHE output allows leveraging the contrast of CLAHE while correcting its illumination distribution.

Second, the adaptive clip limit version outperforms fixed parameter CLAHE with respect to modulation of the clip limit value based on the local texture properties. As can be seen from the sensitivity analysis (Fig. 6), medium adaptability brings some improvements in terms of entropy and chroma accuracy.

Third, the comparative study places the introduced technique above HE, isolated CLAHE, and single scale Retinex techniques, although it cannot compete with deep learning algorithms in terms of performance on benchmarks. As one can see from the comparative table (Table II), the choice of method is dictated by application requirements: deep algorithms for highest quality if possible; hybrid classical methods otherwise.

Limitations of this approach need to be clearly stated. It cannot be used for haze removal, denoising or super resolution; it deals with contrast and illumination improvements only. Performance in cases of highly corrupted images such as underwater or night vision images with high noise floor will be worse than specialized approaches. The guided filter parameters and regularization factors were selected experimentally and can differ for atypical images in terms of spatial statistics.

Two directions for future work can be identified. First, addition of light-weight noise estimation will allow using the proposed approach for low-light images without decrease in efficiency. Second, perceptual validation based on human observer study will provide supplementary results to the results presented here, especially for aesthetic purposes. To summarize, the proposed hybrid approach CLAHE-Retinex demonstrates the relevance and usefulness of classical enhancement methods when properly combined and adaptively parameterized.

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