Evaluation of Histogram-Based Image Enhancement Methods for Facial Images in Drowsy Driver Using No-Reference Metrics

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Article Info

ABSTRACT

Low-light facial images suffer significant quality degradation, leading to performance degradation in surveillance and face recognition systems, where conventional enhancement methods often produce over-enhancement or unnatural noise artifacts. This study compares three histogram equalization methods, namely HE, AHE, and CLAHE, for low-light facial image enhancement, with evaluation using no-reference quality assessment metrics, including NIQE, LOE, and Entropy, as well as visual analysis and histogram distribution. The results showed that AHE produced the lowest NIQE (4.96 ± 1.38) and the highest entropy (7.86 ± 0.11) but had significant noise artifacts, HE produced an overly even distribution with NIQE of 6.34 ± 1.41, while CLAHE showed the most balanced performance with the lowest LOE (0.07 ± 0.02) and the best visual quality when using the optimal clip limit in the range of 1.2-2.0, providing an optimal trade-off between contrast enhancement, naturalness preservation, and artifact minimization with computational efficiency below 1 ms.

I. INTRODUCTION

Driving safety is a crucial issue in modern transportation, particularly related to driver fatigue and drowsiness. The Central Statistics Agency (BPS) [1] recorded 150,906 traffic accidents in 2024, resulting in 26,839 fatalities. The National Transportation Safety Committee (KNKT) reported that approximately 60% of these accidents were caused by driver drowsiness [2]. This demonstrates that early detection of driver fatigue and drowsiness is a crucial aspect in improving driving safety.

Various computer vision-based driver monitoring systems have been developed to detect such conditions non-invasively and in real-time [3], [4]. The reliability of these systems is highly dependent on the quality of the images produced by the camera as the primary input, as poor image quality can reduce the accuracy of advanced analysis processes [5], [6], such as detecting the driver's face, eyes, and expressions.

In practice, driver images often experience quality degradation due to uneven lighting, shadows, and dynamic environmental conditions, especially in nighttime driving scenarios or low-light conditions. To address these issues, various image quality enhancement algorithms have been developed, ranging from classical methods to transformation-based methods and model-based and deep learning approaches. Classical methods, such as Histogram Equalization, Adaptive Histogram Equalization, Contrast-Limited Adaptive Histogram Equalization, and Gamma Correction, work directly in the spatial domain with low computational complexity and are easy to implement, but the resulting quality improvement tends to be limited and highly dependent on image characteristics [7], [8]. Transform-based methods, such as Wavelet Transform, Homomorphic Filtering, as well as Fourier or Discrete Cosine Transform (DCT)-based approaches, utilize frequency or multi-scale representations to enhance specific details and contrast, but require careful parameter selection and have higher computational costs [9], [10]. Meanwhile, model-based and deep learning approaches, such as Retinex, Autoencoder, Generative Adversarial Network (GAN), and Deep Curve

Estimation (DCE) methods [14], are capable of producing significant image quality improvements through modeling complex non-linear relationships, but require training data, large computational resources, and are dependent on certain data characteristics, making them less flexible for direct application to real-time systems with hardware limitations [15].

In the context of driver drowsiness monitoring applications that demand computational efficiency, ease of implementation, and the ability to apply directly without additional training processes, lightweight image enhancement methods become more relevant. Therefore, histogram-based contrast enhancement methods are widely used because they are simple, fast, and do not require training data. Commonly used histogram-based methods include Histogram Equalization (HE), Adaptive Histogram Equalization (AHE), and Contrast-Limited Adaptive Histogram Equalization (CLAHE). HE enhances image contrast globally, but potentially neglects local details. AHE enhances contrast locally, but tends to amplify noise. CLAHE limits local contrast enhancement, resulting in more stable image quality, although its performance is still affected by image parameters and characteristics.

In image quality evaluation, most previous studies still rely on full-reference metrics such as Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM), which require reference images [16], [17], [18]. In drowsy driver images, reference images are generally unavailable, making this approach less suitable for real-world conditions. Therefore, a no-reference image quality assessment-based evaluation approach is needed. No-reference metrics such as Perception-based Image Quality Evaluator (PIQE), Lightness Order Error (LOE), and Entropy are chosen because they are more representative in assessing image quality without relying on reference images [19], [20].

Based on these problems, this study aims to compare the Histogram Equalization (HE), Adaptive Histogram Equalization (AHE), and Contrast Limited Adaptive Histogram Equalization (CLAHE) methods in improving the image quality of drowsy drivers using a no-reference image quality assessment approach. Image quality evaluation is evaluated using PIQE, LOE, and entropy metrics to determine the most effective image enhancement method without relying on reference images.

This study is limited to a comparison of histogram-based image enhancement methods. Learning-based or complex model-based image enhancement methods, such as Retinex and Zero-DCE, are not discussed because they require a more complex training process, parameter adjustment, and reliance on specific data characteristics, making them less suitable for the research objectives, which emphasize computational efficiency, objective evaluation, and direct application without additional training. Focusing on histogram-based methods allows for a more controlled and fair comparative analysis of classical, lightweight, and easy-to-implement contrast enhancement techniques.

The results of this study are expected to provide theoretical contributions in the field of image processing, particularly regarding the evaluation of no-reference-based image quality improvement in images of drowsy drivers. Furthermore, this study also provides practical benefits as a reference in selecting effective image enhancement methods to support the development of image-based drowsy driver monitoring and detection systems under non-ideal lighting conditions. A summary of this research flow is further mapped in Table 1 below.

TABLE I
CORRELATION OF RP-RQ-RO

RP (Research Problem)	RQ (Research Question)	RO (Research Objective)
The image quality of drowsy drivers often experiences degradation due to non-ideal lighting, while the selection of the most effective and objective histogram-based image enhancement method without reference imagery remains unclear.	Which histogram-based image enhancement method (HE, AHE, or CLAHE) is most effective in improving the image quality of drowsy drivers based on no-reference image quality assessment metrics?	Conducting a comparative analysis of HE, AHE, and CLAHE methods on drowsy driver images using PIQE, LOE, and entropy metrics to determine the most effective image enhancement method without relying on reference images.

II. METHOD

This study uses a quantitative experimental approach to compare the performance of HE, AHE, and CLAHE methods in improving the image quality of drowsy drivers. Image quality evaluation was performed using a no-reference image quality assessment metric without involving reference images. The experiment was conducted using the Python programming language running on a DGX A100.

A. Research Data and Preprocessing

The data used in this study are images of drowsy drivers obtained from driver dashboard camera recordings from the source of the "Driver Drowsiness Dataset" [21] dataset, totaling 41,793 images, consisting of 22,348 Drowsy images and 19,445 Non-Drowsy images. The image data reflects real conditions, such as low lighting, shadows, and uneven contrast, making it suitable for testing the effectiveness of image enhancement methods. From the data sources obtained, the data has been cut into frames with the VLC software and has been cut into face roi with the Haar cascade technique. Sample datasets can be seen in the following figure 1, which is continued by conversion to the grayscale color space.
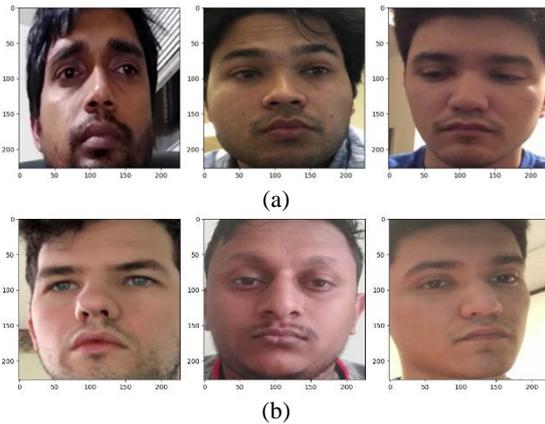

(a)

(b)

Figure 1. Samples from the ddd (*driver drowsiness dataset*) drowsy condition (a) and *non-drowsy condition* (b)

B. Image Contrast Enhancement

This sub-chapter explains the method of each contrast enhancement carried out along with the parameter values used.

1. Histogram Equalization

Histogram Equalization is applied to improve image contrast globally by distributing pixel intensities evenly. This method works by flattening the distribution of pixel values so that they are not only concentrated in a certain range, but are spread evenly across the available intensity range. This process is carried out through a histogram transformation, where low-frequency pixels are amplified, while high-frequency pixels are adjusted so that they are not too dominant. As a result, images that have gone through Histogram Equalization have better contrast and clearer details, thus facilitating the process of visual analysis and interpretation [22]. This technique is widely used to improve image quality in various applications, such as object detection, pattern recognition, and medical image processing. It is carried out using the following equation 1 formula:

$$h_i = \frac{n_i}{n}, i = 0,1,2 \cdots, L-1 \qquad (1)$$

Where, L is the gray level, ni is the number of pixels with gray level, i, and n is the sum of all pixels [7].

2. Adaptive Histogram Equalization

Aimed at enhancing contrast locally by dividing the image into several small areas. Adaptive Histogram Equalization (AHE) is a development of histogram equalization techniques that works on a similar principle. AHE, also known as local histogram processing [23], performs histogram equalization locally on several small parts of the image. This process is done by dividing the image into several blocks or sub-images, then applying histogram equalization to each block. The block size used in this study is 8x8. This algorithm is described in equation 2.

$$H_{(i)} = \sum x, y \in tile \; p(i, x, y) \qquad (2)$$

Where, $H_{(i)}$ is the histogram for intensity i and $p(i, x, y)$ is the number of pixels in a tile with intensity i.

3. Contrast Limited Adaptive Histogram Equalization

This is an extension of AHE that limits local contrast enhancement to reduce noise amplification. All three methods were applied to the same image to ensure a fair comparison. The block size used was 8x8, and the clip limit value was random in the range of 0.5-2.0, as described in equation 3.

$$\beta = \frac{M}{N} \left(1 + \frac{\alpha}{100}(S_{max} - 1)\right) \qquad (3)$$

In this context, M represents the area of the region size, N signifies the grayscale value (often 256), α is the clipping factor that modifies the histogram limit boundary, and $Smax$ describes the maximum achievable pixel value after the application of CLAHE. According to Equation 3 [6], the controlled contrast enhancement provided by CLAHE with a clip limit is expected to substantially improve image quality by yielding more accurate, detailed results.

C. Image Quality Evaluation

Image quality evaluation is performed using several no-reference metrics and computation time. These include the following:

1. Perception-based Image Quality Evaluator (PIQE)

PIQE is a no-reference metric that evaluates image quality based on human perception without requiring a reference

image. This metric analyzes local distortion through spatial activity and block-level distortion. A low PIQE value indicates good image quality with minimal distortion. PIQE effectively detects various types of degradation such as blur, noise, and compression artifacts. The PIQE value range is 0-100, where values close to 0 indicate excellent quality and high values indicate poor quality. PIQE is explained in equation 4 below.

$$PIQE = C_1 \cdot D_{NSA} + C_2 \cdot S_{block} \qquad (4)$$

Where C_1, C_2 is the weighting constant, D_{NSA} deviation from Noticeably Significant Activity, and S_{block} spatial variation of the image blocks.

2. Lightness Order Error (LOE)

The LOE measures the degree of brightness order distortion caused by image enhancement. It measures how much the relative brightness order between pixel pairs changes after the enhancement process. A low LOE value indicates that the enhancement method is able to maintain the natural brightness order of the original image, meaning no significant order reversal occurs. This metric is important to ensure that enhancement does not produce artifacts or unnatural distortions. The ideal LOE value is 0, which means no order change at all, as described in equation 5 below.

$$LOE = \frac{1}{n} \sum_{i=1}^{n} RD(i) \qquad (5)$$

Where n is the total number of pixels in the image, while is $RD(i)$ the relative order difference for the i-th pixel.

3. Entropy

Entropy is used to measure the information content of an image. All of these metrics do not require a reference image, thus aligning with the characteristics of the research data. Shannon Entropy is calculated from grayscale histograms, using the following equation 6.

$$H = -\sum_{i} p(i) \log_2 p(i) \qquad (6)$$

Where $p(i)$ represents the probability of intensity level i. Higher entropy indicates richer information content

D. Analysis of Results

The evaluation results for each method were quantitatively analyzed by comparing PIQE, LOE, and entropy values, followed by an analysis of computational time. Image enhancement methods that produced lower PIQE and LOE values and higher entropy were considered to have better image quality. This analysis was used to determine the most effective image enhancement method for drowsy driver images.

III. RESULTS AND DISCUSSION

This chapter presents and discusses the performance analysis results of the image contrast enhancement techniques tested within a face-based driver drowsiness detection framework. Two analyses are performed: a no-reference evaluation matrix analysis and a visual evaluation and histogram analysis. Details of each technique's performance are shown in Table II.

TABLE II
NO-REFERENCE METRIC EVALUATION RESULTS

Algorithm	Average			
	NIQE	LOE	Entropy	Time (s)
HE	6.34 $\pm$1.41*	0.01 $\pm$0.01	7.13 $\pm$0.31	0.000050 $\pm$0.000011*
AHE	4.96 $\pm$1.38	0.27 $\pm$0.03	7.86 $\pm$0.11*	0.000253 $\pm$0.000185
CLAHE	6.84 $\pm$1.70	0.07 $\pm$0.02*	7.51 $\pm$0.26	0.000249 $\pm$0.000198
Original	7.72 $\pm$1.68	-	7.29 $\pm$0.31	-

The no-reference evaluation results show that all algorithms have advantages for each matrix compared to the original image, where AHE excels in producing the highest information richness with the highest average Entropy value (7.86) and the best perceptual quality according to the NIQE metric (the lowest, 4.96), but its advantages are overshadowed by its significant weakness in image authenticity, as evidenced by the highest LOE value (0.27) and the relatively slowest computation time (0.000253 seconds). In contrast, CLAHE (Contrast Limited AHE) achieves an optimal balance between the three factors; despite having a worse average NIQE score (6.84) than AHE, indicative of contrast limitation CLAHE is much more effective in preserving the brightness

integrity of the original image with a very low LOE value (0.07), only slightly worse than HE (0.01) and significantly better than AHE, while maintaining a computational time efficiency comparable to AHE (0.000249 seconds). Meanwhile, HE (Histogram Equalization) shows superior computational efficiency (0.000050 seconds) and best originality preservation (LOE 0.01), but produces the least Entropy increase (7.13) and moderate NIQE score (6.34), indicating that this method is less aggressive in improving the overall visual quality than the other two adaptive methods.

Although the AHE method achieved the highest Entropy value (7.86) and the lowest NIQE score (4.96), which nominally indicate the best perceptual quality, further data

analysis revealed unacceptable trade-offs in the applied domain. The high LOE value (0.27) of AHE, which is significantly worse than that of CLAHE (0.07), quantitatively proves that AHE causes severe distortion of the image brightness integrity. This is supported by visual observation of noise and block artifacts. Therefore, the low NIQE score of AHE should be interpreted with caution as a result of extreme contrast enhancement, rather than as superior perceptual quality, as the method fails to meet the criterion of authenticity preservation. Then, the distribution of the results of each evaluation matrix can be seen in Figure 2 below.
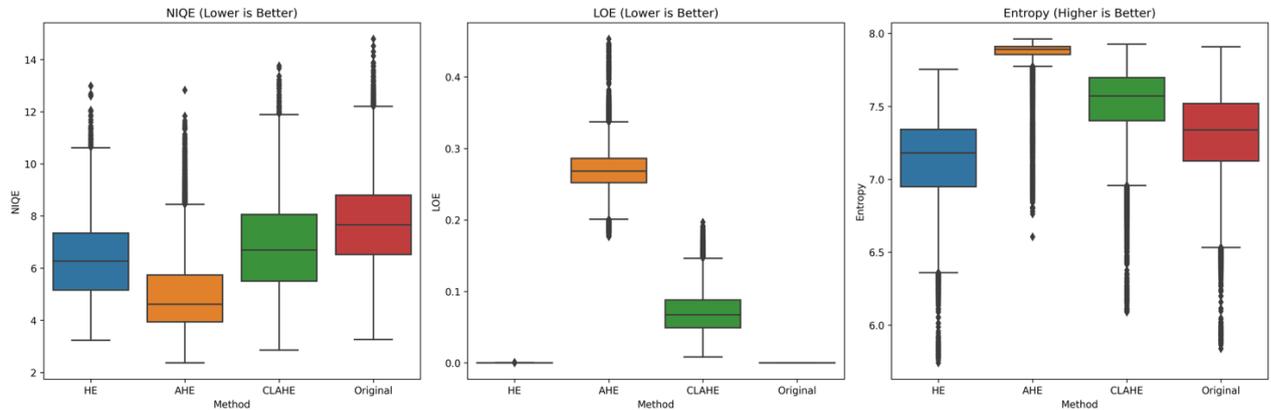

Figure 2. Methods comparison box-plot metrics

Figure 2 shows the distribution of values for each evaluation metric, indicating that the AHE algorithm has the most outliers of all metrics, indicating that the method is less stable. CLAHE results on NIQE tend to be stable in terms of outliers, HE is most stable in LOE, and Entropy in terms of its outlier gap. Based on this analysis, further visual analysis was performed, as can be seen in Figure 3 below.
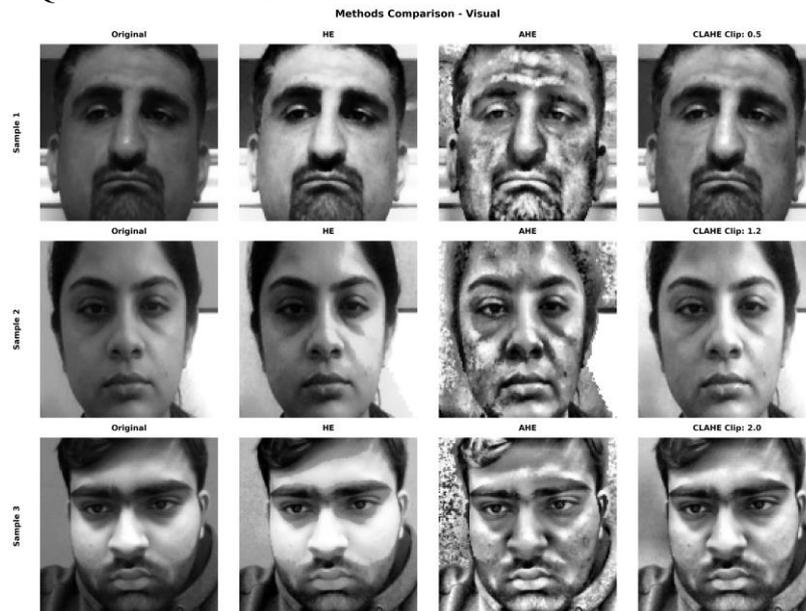

Figure 3. Visual comparison methods from sample data

Visually, a comparison of the three samples shows that the enhancement methods produce different characteristics in image quality. The original images in all samples have low contrast with less clear details and dominant shadows in the eye area. The HE method successfully increases contrast globally, but produces a posterization effect in smooth areas and a halo effect at the dark-light border, as well as blown highlights in several regions. AHE, which does not have a clip limit, shows poor results with severe artifacts in the form of highly visible salt-and-pepper noise, grid patterns, over-enhancement textures, and excessive noise amplification, making the image look unnatural.

CLAHE shows the best visual performance with results that are highly dependent on the choice of clip limit. A low clip limit (0.5) is effective for images with smooth gradation, such as facial images, producing clear facial details with natural skin texture without noise. A medium clip limit (1.2) is optimal for images with uneven lighting, able to increase

contrast in a balanced way where dark regions are enhanced without artifacts and bright regions remain natural. A higher clip limit (2.0) is suitable for low-contrast images with fine details, successfully increasing visibility and micro-contrast while preserving smooth transitions without posterization. CLAHE maintains the naturalness of the image with good local adaptive enhancement, not producing blurring effects like HE or noise amplification like AHE. CLAHE's ability to adapt enhancement based on local characteristics and precise clip limit control makes it an optimal method for various image conditions, provided that the clip limit is adjusted to the specific characteristics of the input image. For visual details of the image, see Figure 4 below. For visual details of the image, see Figure 4 below.
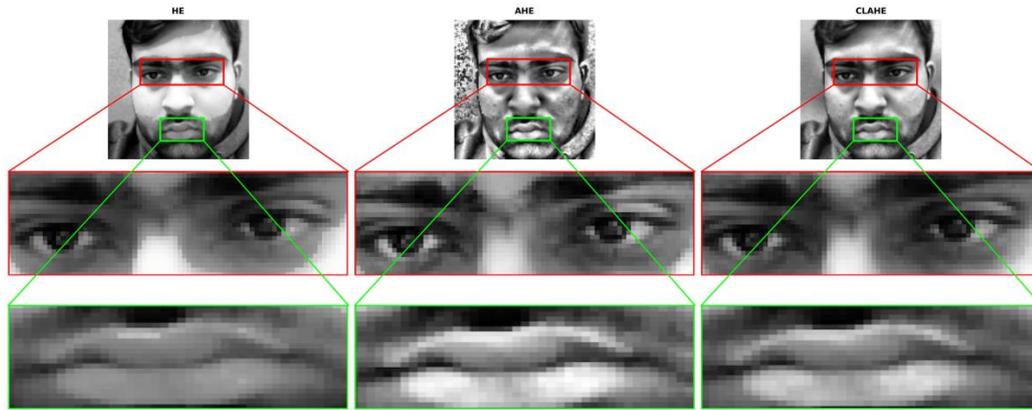

Figure 4. Visual comparison of roi of each method

Figure 4 displays a comparison of enhancement results using the HE, AHE, and CLAHE methods with a focus on two Region of Interest (ROI) areas, namely the eye area (red box) and the mouth area (green box). From this visualization, it can be seen that the HE method produces quite good contrast but tends to over-enhancement in bright areas such as the nose. The AHE method shows a significant increase in local detail, but produces clearly visible noise especially in areas of the face characterized by a mottled texture. Meanwhile, the CLAHE method produces the best balance between increasing contrast and reducing noise, where details in the eye and mouth areas are well preserved without producing excessive artifacts, so the image looks more natural and maintains important visual information for further analysis. Then, for further analysis, it is continued with the analysis of the image histogram results, which can be seen in Figure 5.

The statistical analysis of the histogram in Figure 5 shows the different characteristics of each enhancement method. In Sample 1 with a low original mean (81.49 ± 47.05), HE and AHE increase the mean to 128.41 and 131.85 with high std (73.43 and 63.14) and a full range of 0-255, but the histogram shows gaps, spikes, and excessive flattening. CLAHE clip 0.5 provides moderate enhancement (mean 112.57 ± 57.02) with shadow detail preservation (min = 10), the histogram is more controlled for smooth gradation images. Sample 2 with original mean 118.97 shows CLAHE clip 1.2 produces the highest mean (151.83 ± 68.17) with range 7-255, and the histogram maintains a balanced bimodal structure for uneven lighting. Sample 3 with a narrow original range (16-252), HE and AHE achieve a mean of ~128-131 with a full range, but the histogram shows blown highlights and over-uniformity, while CLAHE clip 2.0 (mean 129.98 ± 60.66, range 10-255) produces a well-balanced distribution that preserves micro-contrast. CLAHE with adaptive clip limit (0.5-2.0) is proven to be optimal in balancing enhancement and preservation of natural characteristics without extreme crushing or blowing like HE and AHE.
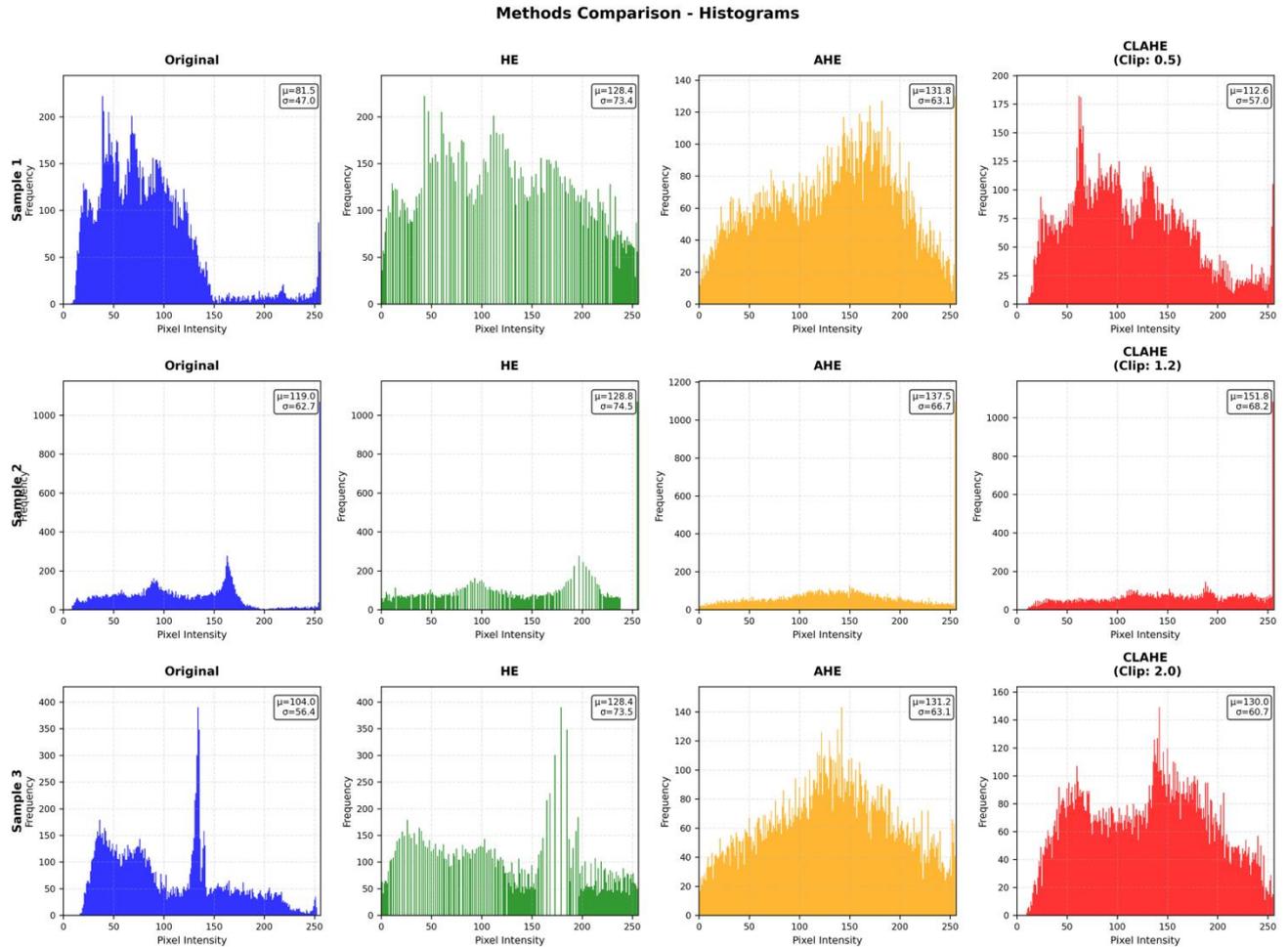
Figure 5. Methods comparison histogram from sample data

Overall, visual and histogram analysis show that CLAHE provides the best results, provided the clip limit is optimally selected according to the image characteristics. A clip limit that is too low (<0.5) may not provide significant enhancement, while a clip limit that is too high (>3.0 or 255.0, like AHE) causes over-enhancement, noise amplification, and artifacts that damage the naturalness of the image. The optimal range of CLAHE clip limits is 0.5-2.5 depending on the characteristics of the input image: images with smooth gradation require a low clip limit (0.5-1.0), images with uneven lighting or mixed content require a medium clip limit (1.0-2.0), and images with very low contrast or heavy shadows can use a higher clip limit (2.0-2.5). The advantage of CLAHE lies in its local adaptive enhancement capability that can accommodate intensity variations within a single image, in contrast to HE, which is global and often results in over- or under enhancement in certain regions, or AHE, which is too aggressive and loses control over noise amplification.

This study limits the scope of comparison to histogram-based contrast enhancement methods, namely HE, AHE, and CLAHE, which share similar characteristics and theoretical underpinnings. This approach was chosen to ensure fair and consistent comparisons within a reference-free evaluation framework. Comparisons with other methods from different paradigms will be a future research direction.

IV. CONCLUSION

This study evaluated the performance of HE, AHE, and CLAHE for low-light facial image enhancement using objective quality metrics and visual assessment. AHE achieves the lowest NIQE value (4.96 ± 1.38) and the highest entropy (7.86 ± 0.11), indicating improved naturalness and information distribution; however, this improvement is accompanied by increased noise and reduced tonal stability. CLAHE yields the lowest LOE (0.07 ± 0.02), demonstrating superior preservation of local brightness while maintaining balanced contrast enhancement, making it more suitable for facial images. The performance of CLAHE is highly sensitive to the clip limit parameter. Moderate values in the range of 1.2–2.0 provide the best trade-off between contrast enhancement, natural appearance, and artifact suppression, whereas lower values result in limited enhancement and higher values introduce noise. All evaluated methods exhibit high computational efficiency with execution times below 1

ms. HE is the fastest (0.000050 ± 0.000011 s), while AHE and CLAHE show comparable runtimes of approximately 0.00025 s, confirming their suitability for real-time applications.

This study has limitations, including a limited dataset, a focus on low-light facial images that are not too extreme, a random selection of CLAHE clip limits that are not optimal for each image, and evaluation using no-reference metrics that do not always correlate perfectly with human subjective assessments. For further research, it is recommended to develop an adaptive method for determining CLAHE clip limits based on input image characteristics using deep learning-based parameter optimization, to evaluate using subjective metrics such as Mean Opinion Score (MOS), and to assess its impact on computer vision tasks such as classification.

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