A Lightweight Training-Free Image Enhancement Method for Traditional Sikka Ikat Motifs Using Log-Gabor Enhanced CLAHE (LGE-CLAHE)

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ABSTRACT

Image enhancement is essential to make subtle motifs in traditional Sikka ikat more visible, where uneven illumination and complex woven textures often hinder effective contrast enhancement. To address this challenge, this paper proposes a training-free and computationally lightweight image enhancement method, termed Log-Gabor Enhanced Contrast-Limited Adaptive Histogram Equalization (LGE-CLAHE). The proposed method integrates a texture-preserving Log-Gabor branch and a contrast-regulating CLAHE branch through a histogram-guided, block-wise adaptive weight map $\alpha(x, y)$ derived from local luminance statistics. Unlike fixed-weight hybrid schemes, the proposed adaptive fusion dynamically adjusts each branch's contribution based on spatial texture variation, enabling robust enhancement under non-uniform illumination without requiring training data. The proposed method is evaluated on a dataset of 432 Sikka ikat images representing 24 traditional motifs, captured under morning, daytime, and night lighting conditions. Experimental results demonstrate that LGE-CLAHE consistently outperforms classical enhancement methods and single-branch baselines, achieving a PSNR of 24.31 dB, an SSIM of 0.961, and an MAE of 0.051. Visual evaluations further confirm that the proposed method enhances motif clarity while avoiding common artifacts such as haloing, block boundaries, and excessive contrast amplification. Owing to its training-free design and low computational complexity, LGE-CLAHE is well-suited to cultural heritage documentation and other low-resource image enhancement applications.

Keywords-LGE-CLAHE; Sikka ikat; Log-Gabor filter; contrast enhancement; texture preservation

I. INTRODUCTION

Preserving cultural heritage, including traditional Sikka ikat weaving motifs, is essential to maintaining regional identity and protecting local traditions. Woven fabrics encode cultural, symbolic, and structural information that can be systematically analyzed through digital image processing techniques to support documentation, analysis, and long-term preservation efforts [1-3]. However, images of ikat fabrics frequently suffer from non-uniform illumination, low contrast, and acquisition noise, which obscure fine woven structures and reduce both visual interpretability and reliability of automated analysis [4]. Similar challenges have been reported in low-light imaging studies, where spatially varying illumination degrades visibility, especially in textured regions [4, 5]. These issues are further amplified in woven textiles, where dense repetitive patterns rely on subtle intensity variations that are easily lost under challenging conditions.

Image enhancement in the spatial domain, particularly through histogram-based methods, remains one of the most widely used approaches for improving visibility and structural clarity in degraded images. According to [6], spatial-domain enhancement manipulates pixel intensities directly and is especially effective for contrast manipulation and feature strengthening in illumination-affected images. Classical techniques such as Histogram Equalization (HE), Adaptive Histogram Equalization (AHE), and Contrast-Limited Histogram Equalization (CLAHE) have been used extensively for low-correction [7-9]. However, CLAHE is highly sensitive to two hyperparameters, the region size and clip limit, where improper selection may oversmooth textures or introduce artifacts [9]. Recent studies further demonstrate that CLAHE performance can be significantly improved through automated or optimized hyperparameter selection. Multi-objective optimization frameworks, such as the cuckoo-search-based parameter tuning proposed in [10], highlight the importance of adaptive parameter regulation for achieving stable enhancement under heterogeneous illumination. Training-free enhancement strategies have therefore gained increasing interest due to their robustness and independence from supervised data [11-13].

Log-Gabor filters, characterized by their zero-DC component and frequency response, offer strong preservation of repetitive high-frequency structures and robustness under varying illumination [14-16]. At the same time, CLAHE and its improved variants continue to demonstrate capability for local contrast regulation across diverse imaging domains [8]. Adaptive weighting framework and pixel-wise fusion strategies have also proven effective for balancing texture preservation and contrast enhancement in heterogeneous regions, emphasizing the importance of a region-adaptive weight map [17] and fine-detail preservation contrast regulation techniques [18].

Despite these advances, several challenges remain unresolved. Classical contrast enhancement methods and adaptive histogram-based techniques often struggle to preserve fine-woven textures under non-uniform illumination. At the same time, texture-oriented approaches, such as Log-Gabor filtering, may enhance detail at the expense of balanced global contrast. Although hybrid enhancement strategies have been proposed, many rely on fixed fusion ratios or handcrafted weighting schemes, limiting their adaptability to spatially varying texture and illumination conditions. Moreover, recent learning-based solutions typically require training data and substantial computational resources, which limit their applicability in lightweight, resource-constrained cultural heritage documentation scenarios.

Motivated by these observations, this study proposes a training-free and computationally lightweight adaptive enhancement framework, termed Log-Gabor Enhancement CLAHE (LGE-CLAHE). The key novelty of the proposed method lies in its block-wise adaptive fusion strategy, where a histogram-guided weight map $\alpha(x,y)$, derived from local luminance statistics, dynamically balances texture preservation and contrast enhancement without relying on fixed weights or training data. This design enables robust enhancement of traditional Sikka ikat motifs under uneven illumination while maintaining fine structural details, thereby addressing the identified research gap.

II. METHODOLOGY

A. Proposed Method

In this work, the input RGB images are first converted into the YCbCr color space, and only the luminance component (Y) is processed by the proposed enhancement framework. The Y channel represents perceptual brightness information, which is most relevant for contrast and texture enhancement, while the chrominance components (Cb and Cr) are preserved to avoid color distortion. After enhancement, the processed luminance is recombined with the original chrominance channels to reconstruct the final RGB output.

The proposed LGE-CLAHE method operates on the luminance component Y of the input image. This technique is based on two complementary principles: Log-Gabor filters are effective for representing high-frequency textures due to their logarithmic frequency response and zero DC component, and CLAHE provides robust local contrast enhancement through adaptive histogram equalization.

When applied independently, Log-Gabor filtering may produce unstable global contrast, while CLAHE may oversmooth repetitive textures. To address these limitations, LGE-CLAHE employs an adaptive fusion strategy in which spatial weights are derived from tile-wise luminance statistics.

B. Log-Gabor-Based Texture Enhancement

The isotropic Log-Gabor radial magnitude is defined as:

$$G(r) = exp\left(-\frac{ln\,(r/f_0))^2}{2(ln(\sigma_f))^2}\right),\ \text{with}\ G(0) = 0 \qquad (1)$$

where f_0, is the center frequency and $\sigma_f > 1$ controls bandwidth. The corresponding spatial kernel is obtained via inverse Fourier transform, $h(x,y) = \mathcal{F}^{-1}\{G)\} - \mu_h$, normalized in ℓ_2 -norm. The Log-Gabor response on the luminance channel component Y is given by:

$$LG(x,y) = Y * h \qquad (2)$$

To ensure a stable dynamic range across different images, the response is percentile-normalized to the interval [0, 1]:

$$LG'(x,y) = clip\left(\frac{LG(x,y)-P_1}{P_{99}-P_1}, 0, 1\right) \qquad (3)$$

where P_1 and P_{99} denote the 1st and 99th percentiles of the Log-Gabor response.

C. CLAHE-Based Local Contrast Enhancement

CLAHE enhances local contrast by applying histogram equalization to small image tiles, following the method in [8] and subsequent variants [19]. The luminance image Y is divided into non-overlapping tiles of size 32×32. Histogram bins are clipped at a predefined threshold, excess pixel counts are redistributed uniformly across bins, the Cumulative Distribution Functions (CDF) are computed, and bilinear interpolation between adjacent tiles yields the contrast-enhanced luminance output $CL(x,y)$.

D. Adaptive Weight Map Computation

In LGE-CLAHE, an adaptive weight map $\alpha(x,y)$ determines the contribution of Log-Gabor and CLAHE enhancements. For each tile b of size 32×32, local luminance variation is measured using the standard deviation:

$$\sigma_b = \sqrt{\frac{1}{N}\sum_{(x,y)\in b}(Y\,(x,y)-\mu_b)^2} \qquad (4)$$

where μ_b is the mean luminance of tile b and N is the number of pixels. The tile-wise adaptive weight is computed as:

$$\alpha_b = \text{clip}\left(\frac{\sigma_b}{\sigma_{max}}, \alpha_{min}, \alpha_{\max}\right) \qquad (5)$$

where σ_{max} is the maximum standard deviation across all tiles, and $\alpha_{min} = 0.10$ and $\alpha_{max} = 0.90$ ensure numerical stability.

Tile-level weighs α_b are then upsampled and smoothed using bilinear interpolation and Gaussian filtering to produce a continuous pixel-wise weight map $\alpha(x,y)$. The design parallels the region-adaptive mechanism used in spatially aware weighting frameworks [20].

E. Adaptive Fusion

To ensure output consistency, reflective padding is applied during the Log-Gabor convolution to avoid boundary artifacts while preserving local texture continuity near image borders. The tile-wise adaptive weights α_b are upsampled to pixel resolution using bilinear interpolation, which provides a smooth transition between neighboring tiles without introducing block discontinuities. Subsequently, a Gaussian smoothing filter with a kernel size of 5×5 and a standard deviation $\sigma = 1.0$ is applied to the upsampled weight map to suppress abrupt spatial variations further and ensure stable fusion across the image. The final enhanced luminance output is computed through convex adaptive fusion:

$$O(x,y) = \alpha(x,y).LG(x,y) + \big(1-\alpha(x,y)\big).CL(x,y) \qquad (6)$$

where $O(x,y) \in [0,1]$. This formulation ensures smooth transitions across regions, preserving fine textures in detail-rich areas while maintaining stable contrast in smoother regions.

F. Overall Workflow and Algorithm

Figure 1 shows an overview of the proposed LGE-CLAHE framework. Input RGB images are converted to the luminance component Y, enhanced separately by the Log-Gabor, CLAHE, and adaptively fused using the pixel-wise weight map $\alpha(x,y)$. The fused luminance is recombined with chrominance channels to produce the final enhanced output. The method is computationally lightweight, requiring only a single convolution operation, histogram-based processing, and convex blending, as shown in Figure 2. To analyze the influence of main design parameters on enhancement quality and computational efficiency, an ablation study was conducted by changing the Log-Gabor kernel size (31, 51, and 71), the CLAHE tile size (16, 32, and 64), and the normalization parameter σ_{max} (30, 50, 80, and 120).

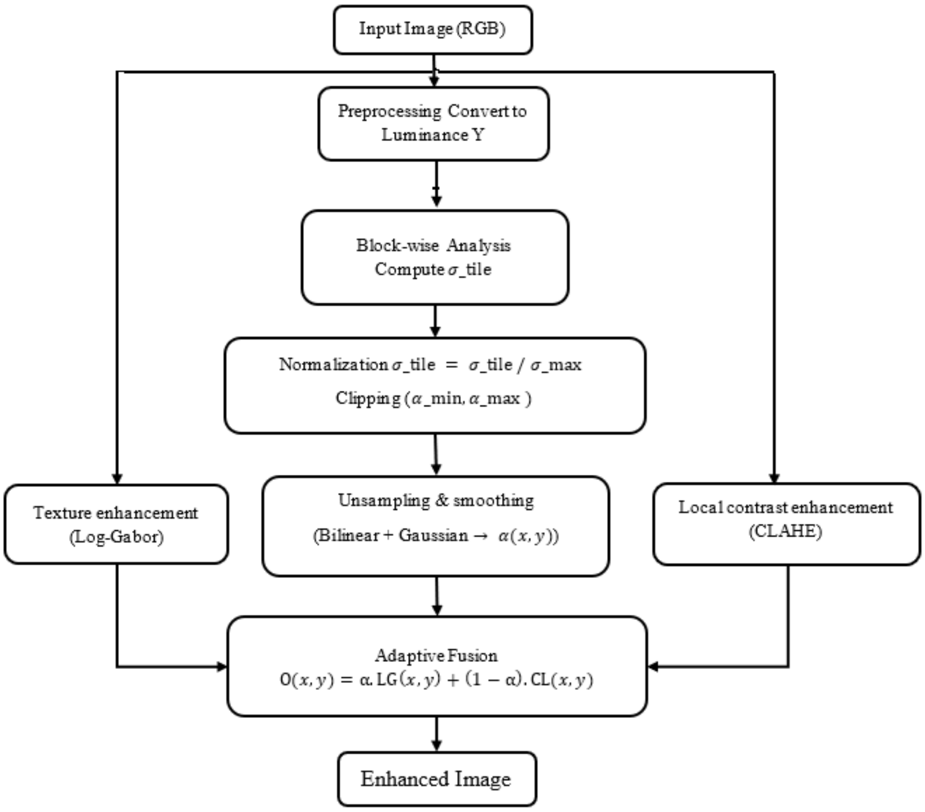

Fig. 1. Overall workflow of the proposed LGE-CLAHE framework.

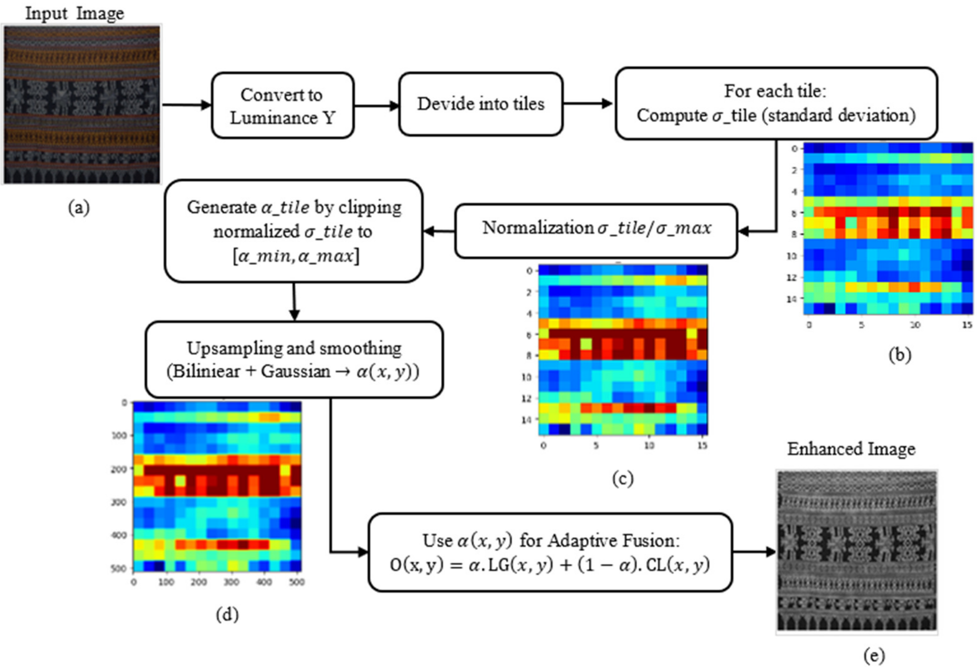

Fig. 2. Adaptive weighting mechanism in LGE-CLAHE: (a) Original image, (b) σ_tile map, (c) α_tile, (d) pixel-wise $\alpha(x,y)$, (e) final enhanced result.

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Algorithm: LGE-CLAHE (training-free
adaptive local fusion)
Input: RGB image $I$
Output: Enhancement image (O)
Convert $I$ to luminance $Y \in [0,1]$
Apply CLAHE with tile size and clip
  limit to obtain CL
Apply Log-Gabor filtering with kernel
  size, followed by percentile
  normalization to obtain LG
Compute tile-wise $\sigma_b$, normalize by
  $\sigma\_max$, clip to $[0.10, 0.90]$, upsample and
  smooth to obtain $\alpha(x,y)$
Fuse outputs:
  $O(x,y) = \alpha(x,y).LG(x,y) + (1-\alpha(x,y)).CL(x,y)$
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For clarity and reproducibility, Table I summarizes all default parameter values used in the main experiments of the proposed LGE-CLAHE framework.

TABLE I. DEFAULT PARAMETER SETTINGS USED IN THE PROPOSED LGE-CLAHE METHOD

Parameter	Value	Description
Image size	512×512	Fixed luminance resolution
Log-Gabor Kernel size	51×51	Spatial kernel
Center frequency f_0	0.15	Radial center frequency
Bandwidth (σ_f)	1.6	Log-Gabor bandwidth
Percentile normalization	P_1, P_{99}	Dynamic range clipping
CLAHE tile size	32×32	Local histogram tiles
CLAHE clip limit	2.0	Contrast limiting
σ_max	80	Weight normalization cap
α range	[0.10, 0.90]	Fusion weight bounds
Gaussian smoothing	5×5	Weight map smoothing

III. EXPERIMENTS

Before enhancement, all images were preprocessed to ensure consistent experimental conditions. Each RGB image was resized to a fixed spatial resolution of 512×512 pixels. The images were converted from RGB to YCbCr, and only the luminance channel (Y) was processed by the proposed method. Luminance values were normalized to the range [0, 1] before applying Log-Gabor filtering, CLAHE, and adaptive fusion. The chrominance channels were preserved and recombined with the enhanced luminance to produce the final RGB output.

Unless otherwise stated, all experiments were conducted using a fixed baseline configuration. The Log-Gabor filter used a 51×51 kernel with a center frequency $f_0 = 0.15$ and a bandwidth parameter $\sigma_f = 1.6$. CLAHE was applied using a tile size of 32×32 and a clip limit of 2.0. The adaptive fusion weight $\alpha(x,y)$ was computed from tile-wise luminance standard deviation, normalized by α_{max}, and constrained to the range [0.10, 0.90]. These parameters were kept constant across all experiments to ensure fair comparison and reproducibility.

A. Datasets

The motif Sikka ikat woven dataset used in this study was collected directly by the author through controlled image acquisition of 24 traditional weaving motifs under three illumination conditions: morning, noon, and night, to reflect real-world variability. The dataset contains 432 RGB images, with six images per class for each illumination setting, and is publicly available [21]. All experiments were conducted using this dataset. This results in a balanced distribution of 144 images per lighting condition, as shown in Table II.

TABLE II. IMAGE DISTRIBUTION BASED ON LIGHTING CONDITIONS

Lighting	Number of Images	Percentage (%)
Morning	144	33.33
Noon	144	33.33
Night	144	33.33
Total	432	100

B. Results

Table III summarizes the results of the evaluation on the 432 Sikka ikat images.

TABLE III. METHOD COMPARISON ON LUMINANCE Y AT 512×512

Method	PSNR	SSIM	MAE	Entropy Y	CII Y	CEM Y	Grad Y
HE	14.061	0.774	0.180	7.928	1.026	1.913	0.943
AHE	19.901	0.893	0.081	7.664	1.020	1.624	0.994
CLAHE	20.281	0.901	0.079	7.665	1.017	1.579	0.960
Log-Gabor	21.832	0.825	0.063	7.400	1.001	0.790	0.500
LGE-CLAHE	**24.310**	**0.961**	**0.051**	**7.560**	**0.999**	**1.173**	**0.765**

The LGE-CLAHE output demonstrates improved luminance balance across the entire fabric while preserving the original fine textures of the Sikka ikat motif. The adaptive weight $\alpha(x,y)$ prevents over-enhancement in smooth regions and selectively strengthens high-frequency structures, resulting in clearer motifs, better tonal uniformity, and preserved periodic patterns.

Representative Sikka ikat samples under challenging illumination conditions demonstrate that CLAHE improves local contrast but tends to over-smooth periodic woven structures. At the same time, Log-Gabor enhancement emphasizes textures but often results in unbalanced global contrast. Conversely, the proposed LGE-CLAHE method achieves a more balanced enhancement, simultaneously improving contrast and preserving fine structural details across varying illumination conditions (Figures 3-4).

(a) (b) (c) (d)

Fig. 3. Visual comparison of a representative Sikka ikat motif captured under outdoor night-time illumination: (a) Original image, (b) Log-Gabor result, (c) CLAHE result, (d) LGE-CLAHE result.

C. Ablation Study

Ablation results indicate that variations in kernel size, tile size, and σ_{max} have a direct impact on the trade-off between enhancement quality and computational efficiency. As summarized in Tables IV-VI, medium-scale parameter settings achieve the most stable performance by preserving fine texture details without introducing boundary artifacts or unnecessary computational overhead, resulting in the best overall balance among the evaluated configurations.

TABLE IV. ABLATION: KERNEL SIZE

Kernel size	PSNR	SSIM	MAE	Entropy Y	CII Y	CEM Y	Grad Y
31	24.312	0.96060	0.05053	7.5596	0.99990	1.1729	0.7644
51	24.309	0.96059	0.05055	7.5597	0.99987	1.1728	0.7647
71	24.305	0.96058	0.05056	7.5599	0.99985	1.1726	0.7651

TABLE V. ABLATION: TILE SIZE

Tile size	PSNR	SSIM	MAE	Entropy Y	CII Y	CEM Y	Grad Y
16	24.325	0.96034	0.05044	7.5589	0.99994	1.1712	0.7633
32	24.321	0.96033	0.05046	7.5590	0.99982	1.1710	0.7636
64	24.318	0.96032	0.05048	7.5592	0.99990	1.1709	0.7640

TABLE VI. ABLATION: σ_max

σ_max	PSNR	SSIM	MAE	Entropy Y	CII Y	CEM Y	Grad Y
30	23.145	0.94325	0.05806	7.57992	1.00219	1.2635	0.8050
50	23.144	0.94327	0.05807	7.57996	1.00217	1.2632	0.8052
80	23.143	0.94326	0.05808	7.58002	1.00215	1.2630	0.8054
120	23.141	0.94325	0.05809	7.58009	1.00213	1.2628	0.8056

IV. DISCUSSION

Across the conducted experiments, LGE-CLAHE consistently improved over the conventional image enhancement approach on the Sikka ikat dataset. As shown in Table II, LGE-CLAHE achieves the highest PSNR and SSIM and a lower MAE than the conventional enhancement approaches. These improvements reflect the method's ability to enhance visual quality without introducing excessive distortion or artifacts. Sikka ikat motifs exhibit dense and repetitive texture patterns resulting from traditional weaving techniques and material characteristics. Such patterns require enhancement methods that preserve fine-grained details while avoiding block artifacts or halo effects. Visual results confirm that LGE-CLAHE effectively restores subtle motif structures and tonal variations under both indoor and outdoor low-light conditions, while maintaining smooth transitions across different regions. This configuration effectively restores repetitive motif details and fine textures without causing halos or discontinuities between blocks, as shown in Figures 3-4. The observed performance gains are primarily attributed to the spatially adaptive weighting mechanism governed by the weight map $\alpha(x,y)$. Computing local luminance variation through tile-wise standard deviation, $\alpha(x,y)$ dynamically adjusts the balance between Log-Gabor-based texture enhancement and CLAHE-based contrast regulation. Regions with rich textures receive a more substantial contribution from the Log-Gabor component, whereas smoother areas rely more on CLAHE to stabilize local contrast. This spatial adaptation explains the simultaneous improvement in texture fidelity and contrast consistency. Compared to baseline techniques, histogram equalization and adaptive histogram equalization often produce over-enhancement in bright or dark regions, whereas CLAHE alone may suppress periodic textures. Log-Gabor filtering enhances high-frequency details but does not sufficiently regulate global contrast. The proposed adaptive fusion strategy successfully compensates for these individual limitations, resulting in stable enhancement across varying illumination conditions.

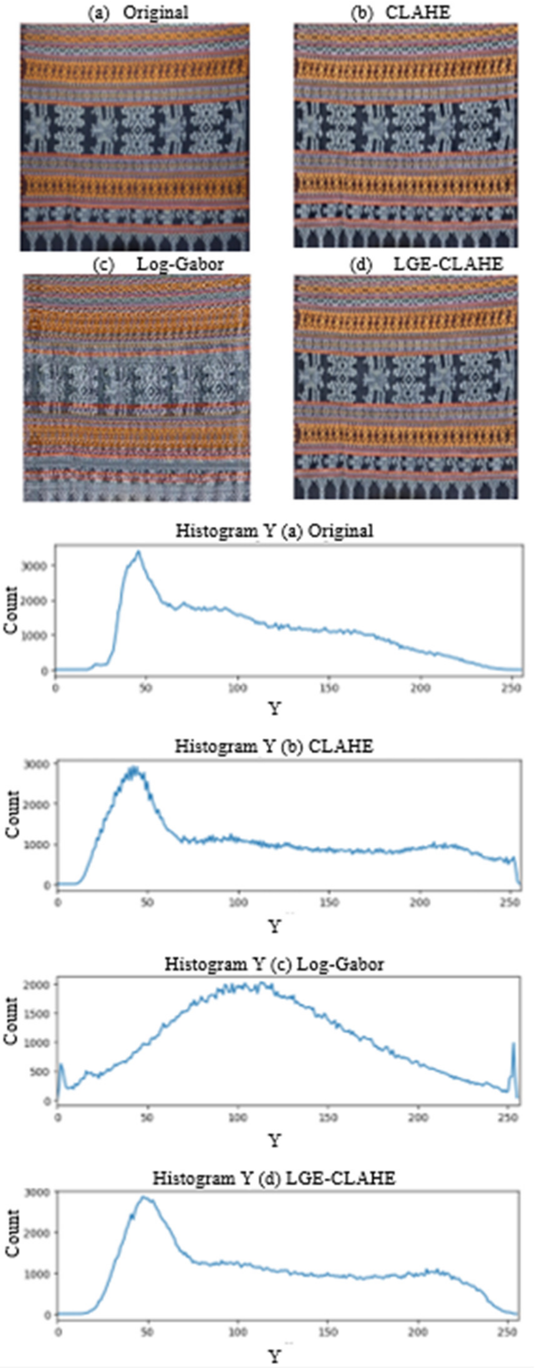

Fig. 4. Visual and histogram-based comparison of a representative Sikka ikat sample: (a) Original image, (b) CLAHE result, (c) Log-Gabor result, and (d) LGE-CLAHE result.

Despite its effectiveness, the proposed LGE-CLAHE framework has several limitations. First, the method relies on local luminance statistics and may be less robust under extreme noise conditions, where noise-induced variance could be misinterpreted as texture. Second, although fixed-parameter values have performed well on the Sikka ikat dataset, performance may vary for images with substantially different textures or imaging conditions. Finally, the proposed method is explicitly designed for textile-like, repetitive patterns; therefore, its effectiveness may be reduced when applied to low-texture, non-textile images, where Log-Gabor responses are less informative.

Ablation experiments further confirm the robustness of the chosen parameter configuration. The combination of a 51×51 Log-Gabor kernel, a tile size of 32×32, and $\sigma\_max = 80$ provides an effective trade-off between enhancement quality and computational efficiency. Smaller kernels or tiles reduce texture representation, while larger settings increase computational cost or risk boundary artifacts. Overall, LGE-CLAHE demonstrates consistent performance across diverse lighting scenarios without requiring training data or complex optimization procedures.

V. CONCLUSION

Despite promising results, several limitations of the proposed LGE-CLAHE framework should be acknowledged. The method relies on a set of fixed parameters that, while shown to be robust across the Sikka ikat dataset, may require adjustment when applied to images with substantially different texture characteristics. In addition, the current evaluation focuses on image quality and does not explicitly analyze execution time or computational complexity on various hardware platforms. Finally, the quantitative assessment is primarily based on a full-reference metric, which may not fully capture perceptual quality in the absence of ground-truth images.

An experimental evaluation on a dedicated Sikka ikat dataset demonstrates that the proposed LGE-CLAHE framework effectively balances texture preservation and contrast regulation via a spatially adaptive fusion mechanism guided by local luminance statistics. By dynamically adjusting the contribution of Log-Gabor filtering and CLAHE across different regions, the method produces visually stable and consistent enhancements under varying illumination conditions.

In contrast to conventional enhancement techniques with fixed parameter settings, LGE-CLAHE enhances fine woven-motif details while suppressing common artifacts such as over-amplified contrast, halos, and block discontinuities. Furthermore, the framework's lightweight design, which relies on a single convolution operation combined with histogram-based processing, makes it particularly suitable for low-resource environments, including practical cultural heritage documentation. Future work may explore extensions, such as multi-orientation Log-Gabor filter banks or image-adaptive parameter selection, to further improve flexibility and scalability for higher-resolution data and broader textile imaging scenarios.

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