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Enhancing visibility of nighttime images using wavelet decomposition with Kekre's LUV color space

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Abstract

Contrast enhancement is a crucial preprocessing method for enhancing the efficiency of subsequent image processing and computer vision tasks. In the past, a lot of effort has been put into improving the visual scenes of pictures taken in low light. Images taken in poor illumination environments frequently reveal issues like color distortion, noise, low brightness, etc., that negatively impact the visual influence on human eyes. Therefore, an approach for improving poorly illuminated images based on wavelet transform is suggested to get around this problem. The input image is first transformed to Kekre's LUV color space, after which discrete wavelet transform (DWT) is applied to part each channel into low and high-frequency components. As the illumination is concentrated on the low-frequency image component, the Exposure-based Sub Image Histogram Equalization (ESIHE) technique is applied to enhance the image's lighting. Besides, limited adaptive histogram equalization (CLAHE) is imposed to control the over-enhancement of specific region's contrast. Modified L, U, and V components are recovered via the inverse discrete wavelet transform (IDWT), and the image is again converted into RGB space. This output is fused with a histogram equalized image using weighted fusion followed by a high boost filter to get the final enhanced output. Experimental outcomes are achieved to validate the efficacy and robustness of the suggested strategy using quality evaluators such as Entropy, NIQE, and BRISQUE rankings explored on ExDark, DPED, and LoLi datasets

Keywords: Contrast enhancement, Histogram equalization, LUV Color space, Discrete wavelet transform, Inverse wavelet transform, Image naturalness.

1. Introduction

Digital images are crucial in practical uses like satellite television, MRIs, computer tomography, and scientific and technological fields like astronomy and geographic information systems. Scientists have struggled to reconstruct the original image contents from disturbing and noisy images in these various disciplines. The goal of image enhancement is to make it easier for viewers to understand the information contained in images.

When an image's contrast is too low, it creates difficulty in viewing its finer features because of uneven or insufficient lighting. To achieve enhanced results, local and global variation consistent with the original intensity as a part of "naturalness preservation" is strived. Researchers have suggested various enhancing techniques to improve the visual appeal of these images or achieve high-visibility effects. Figure 1 shows a sample specimen of low-light images from different datasets.

Histogram equalization (HE), a statistics-based approach, is one of many pixel modulation schemes that directly alter the image's pixel intensity for improvement. Artifacts and a lack of naturalness could result from this kind of approach.

However, the settings require manual construction with past understanding, and the spatial information is not considered while acting on each pixel. The non-linear gamma correction approach greatly performs in challenging light circumstances due to the extensive usage of mapping curves. More inner data of the picture may be acquired with the aid of changing pixel data to different domain names using strategies like discrete Fourier

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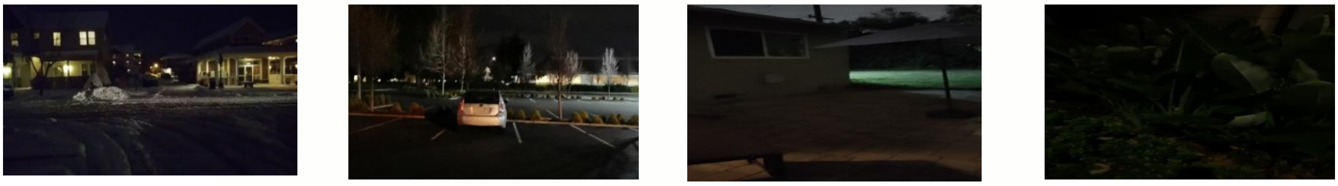
Sample specimen from ExDark Dataset



Sample specimen from LoLi Dataset

Sample specimen from DPED Dataset

transform (DFT), discrete cosine transform (DCT), and discrete wavelet transform (DWT). These solutions, which may damage potentially helpful visual cues, combine spatial reconstruction techniques like homomorphic filtering with frequency-domain filters to produce such effects.

An enhancement method produces an image of higher quality for a specific use, and it can do this by reducing noise or boosting visual contrast. Noise typically taints the data sets that image sensors collect. The relevant data quality may be lowered by unreliable equipment, issues with the data collection procedure, and interfering natural events. Distortions can occur in a variety of ways. One of the most frequent instances is distortion brought on by additive white Gaussian noise, subpar image collection, or sending the image data through noisy communication channels. Impulse and speckle noises are two additional categories of noise.

Additionally, compression and transmission faults also have the potential to cause noise. Thus, denoising is frequently an essential initial step before evaluating the picture data. An effective denoising technique must be used to compensate for such data distortion. Because noise reduction generates artifacts and blurs images, image denoising is still difficult for researchers. An old but current industrial issue is the denoising of electronically distorted images.

The two main ways to denoise images are spatial and transform domain filtering methods. The idea behind spatial filters is that noise is present in the higher frequency spectrum; hence they apply a low pass filter to groups of pixels. Spatial low-pass filters blur edges in signals and images while smoothing away noise, in contrast to high-pass filters, which can sharpen edges and boost spatial resolution while magnifying the noisy background.

The spatial domain approach directly works on pixels, but the transform domain method first performs an image's Fourier transform before returning it to the spatial domain. Pixel values can be changed using the spatial domain method. A new type of signal analysis, wavelet analysis, is much more effective than Fourier analysis when the signal has temporal behavior or discontinuities. Wavelet transforms have been extensively studied for additive noise reduction of signals and images. A scale-based decomposition is provided using the wavelet transform.

Wavelet transforms of images often consist of a limited number of large coefficients and many small coefficients. As a result, there are two probability states for each wavelet coefficient: significant and insignificant. Convolution and lifting scheme methods are used to implement the discrete wavelet transform (DWT) for discrete-time signals. The fundamental process involves downsampling the outputs by a factor of two after applying low and high pass filters.

When the outcome of the low pass channel is subjected to the same decomposition, a two-level wavelet transform results; this method is repeated in a dyadic

transform. The lifting technique can be applied beforehand to enhance or denoise the image and can also be applied in reverse to bring back the original image. This paper is composed of six sections. The existing research on enhancing low-light contrast in dark images is found in Section 2. In Section 3, the recommended Contrast Enhancement method is shown. Section 4 evaluated the suggested method using the ExDark, DPED, and LoLi datasets, which distorts the findings. Section 5 summarizes the whole work, while section 6 focuses on its constraints and potential scope.

2. Literature survey

This section reviews the state-of-the-art techniques for enhancing the quality of degraded images. A few efforts to improve image detail have been published. Multiple input images were acquired under varying lighting conditions, and researchers devised various algorithms using different color spaces in spatial and transform domains.

The technique known as "Histogram Equalization" (HE) is often used to enhance image contrast within a spatial domain set (Gonzalez & Woods, 2002). This approach has a condensed build time and is flexible to use. The histogram equalization process locates the pixel intensities that recur the most frequently and distributes them evenly throughout the image. HE is a particularly helpful technique for spreading intensities uniformly across the entire image because images in the dark have bright and dark regions. This method's drawback is that the output that has been equalized could contain overly bright areas. Two modified versions of the HE approach have been created in response to this restriction: "Adaptive HE" (AHE) (Pizer & Amburn, 1987), and "Contrast Limited Adaptive HE" (CLAHE) (Mhan & Simon, 2020). The mentioned techniques aim to improve results by working on multiple regions with diverse histograms applied to less illuminated photos.

There are numerous methods for figuring out the clipping threshold values in these procedures. "Exposure-based Sub-Image HE" (ESIHE) divides images into

way to produce a multilevel decomposition. The lifting scheme is a more effective wavelet transform technique than the convolution approach of the wavelet

sub-images with different intensities and is used to increase output effectiveness (Singh & Kapoor, 2014). Recently, another approach to enhancing and balancing the brightness of dark images is using Kekre's LUV color space that enhances the brightness of the input image and blends it with the output of HE (Pardhi & Thepade, 2020). The non-uniformly lighted image was split into five sub-images, and a modified method was introduced by giving each histogram's cumulative density function a nonlinear weight correction. The result is a modified intensity mapping for overexposed and underexposed (Hidayah & Ashidi, 2021). Another idea is to use quick local Laplacian filtering that enhances only the local details of the bright and dark regions (FLLF). First, the average brightness for each place is calculated to estimate the region of enhancement (RoE) of every image in the bright and dark parts. The authors employed a multiresolution technique to create the fused image for pixels in the RoE, extracting the darkest or brightest details using the modified faster local Laplacian filtering as the detail extraction mechanism (Wang & He, 2021).

Many authors offer an alternative approach to histograms grounded on the Retinex hypothesis. The algorithms assume the reflection to be a modified outcome by eliminating and estimating the illumination. Using a Gaussian filter, Single Scale Retinex (SSR) (Jobson & Rehman, 1997), Multiscale Retinex (MSR) (Jobson & Rehman, 1997) split reflection and illumination. The lack of lighting improves brightness and detail, but a center/perimeter approach may overemphasize the reported results. MSRCR negates the shortcomings mentioned above. Adaptive Retinex-based technology minimizes halo artifacts by applying adaptive filters to the luminance channels (Meylan & Susstrunk, 2006). As recommended, Multiscale Retinex can also be used in OLED displays that give the right gain for good visibility and save power without flickering artifacts (Yeon, 2006). Another technology focuses on image quality with complex atmospheres. Here, to advance the image quality of photographs, MSR is applied in consideration of image quality learning (Liu & Lu, 2017). A Retinex-based high-speed algorithm (RBFA) has been introduced to restore low-brightness, suppressed content. Here, the original dark

image is changed to a space with a different hue-saturation intensity. This intensity component is stretched using a linear function of dynamic range (Liu, 2021). Recently, a new method that combines color restoration and denoising has been proposed. Here, paired pictures are subjected to modified Retinex-decomposition to produce reflectance and illumination maps. This prevents the use of flexible joint function over smoothing (Yu & Li, 2022).

To improve the brightness of dark photographs, the author used an automatic gamma correction method with luminance pixel probability scattering. To reduce processing complexity, these algorithms use temporary information about the differences between each frame to correct dark images (Huang & Cheng, 2013). By separating the luminance components of the YCbCr color space, a new method of dynamic range adjustment (AMIDRA) and less illuminated image enhancement has been established (Yang & Li, 2018). A new technique called Adaptive Image Enhancement (AIEM) (Wang & Chen, 2019) corrects low-light images by converting RGB images into HSV space and uses Weber-Fechner's law to build intensity components. Based on the distribution profile of the lighting component, the adaptive adjustment for enhancement produces two images. Finally, merging the two images will improve the resulting image. Recently, adaptive gamma correction has been used with Retinex theory. Training sets establish an association between image exposure and features under maximum entropy generation (Yu, 2021). A new improvement algorithm was recently presented that can improve photos close to the boundary of separation and images well within the barrier. Utilizing nonlinear weight modifications, the algorithm's fundamental concept is integrating several AGC-enhancing functions. Using these weight adjustments, both contrast and brightness have been changed (Sengupta & Biswas, 2021).

As proposed by (Demirel & Anbarjafari, 2008) and (Demirel & Anbarjafari, 2010), some frequency domain approaches for enhancing low-contrast images are non-uniform contrast and medium range based on the scaling of individual values. Ideal for bright images. Compared to previous approaches, the methods are (Atta & Ghanbari, 2013) and (Atta & Abdel-Kader, 2015), which improve the performance of photos in the medium brightness range). Another approach to improving dark images by the combination of CLAHE-DWT. To accentuate the low-frequency coefficients and reduce the noise amplification without affecting the high-frequency coefficients, the original image is first divided into low and high-frequency components by DWT. This is so since the high-frequency components comprise the majority of noise in the original image. Finally, get the inverse DWT of new coefficients and reconstruct the image. To avoid over-amplification, the average of the original reconstructed image is used from the originally proposed weighting factor (Lidong & Wei, 2015). In current years, new tactics have been introduced that change the wavelet transform. In this approach, a fuzzy dot matrix and a planar feature matrix are constructed, new values for the gradient mean and image quality index are calculated, and the original image is (Qing & Feng, 2021).

Several techniques based on the fusion process have been presented to improve low-contrast photography. A procedure was introduced to create many photos at different exposures by mapping the intensity function to the input image (Lim & Park, 2006). Combining domain-specific information with a hybrid image enhancement approach produces more detailed, low-noise images. Improve medical images using frequency and spatial domain techniques (Muslim & Khan, 2019). Establishing stability between contrast and brightness using image fusion optimized for cuckoo search is a more advanced technique in this area. Authors first apply a Cuckoo search-based optimization approach to develop an improved photo duo to generate two sets of ideal parameters. The first set has high contrast and sharpness, and the second is bright and detailed without affecting sharpness. The fusion method combines the two improved images to produce a balanced contrast and brightness output (Lalit & Viney, 2021). In the most recent method of improvement, the histogram is divided into three sub-parts, indicating the dark, grey, and brilliant sections of the histogram according to the homogeneity value. Then, local changes in each sub-section are done using 2D geometric scaling and adaptive gamma. The 2D translation technique is used to join these altered sub-sections once more. On the other hand, the entire histogram is given a global gamma transformation. The finishing transformation matrix is then created by integrating the local-global transformations that have already been computed (Sarkar & Halder, 2021).

The need to introduce the proposed method is because of the following limitations of the methods discussed so far are listed below

1. Occurrence of noise and color distortion in an image (Wang & He, 2021)
2. Under enhancement of image in the dark region (Yang & Li, 2018)

3. Loss of details at the edges of an image (Atta & Abdel-Kader, 2015)
4. brightness in some regions where street lights or bright sources are present (Lalit & Viney, 2021)

To overcome the above drawbacks from the existing method, the proposed method is founded on the following key contributions

- Use of Kekre's LUV color space as it improves the quality of recreated colored output image and minimizes color distortion

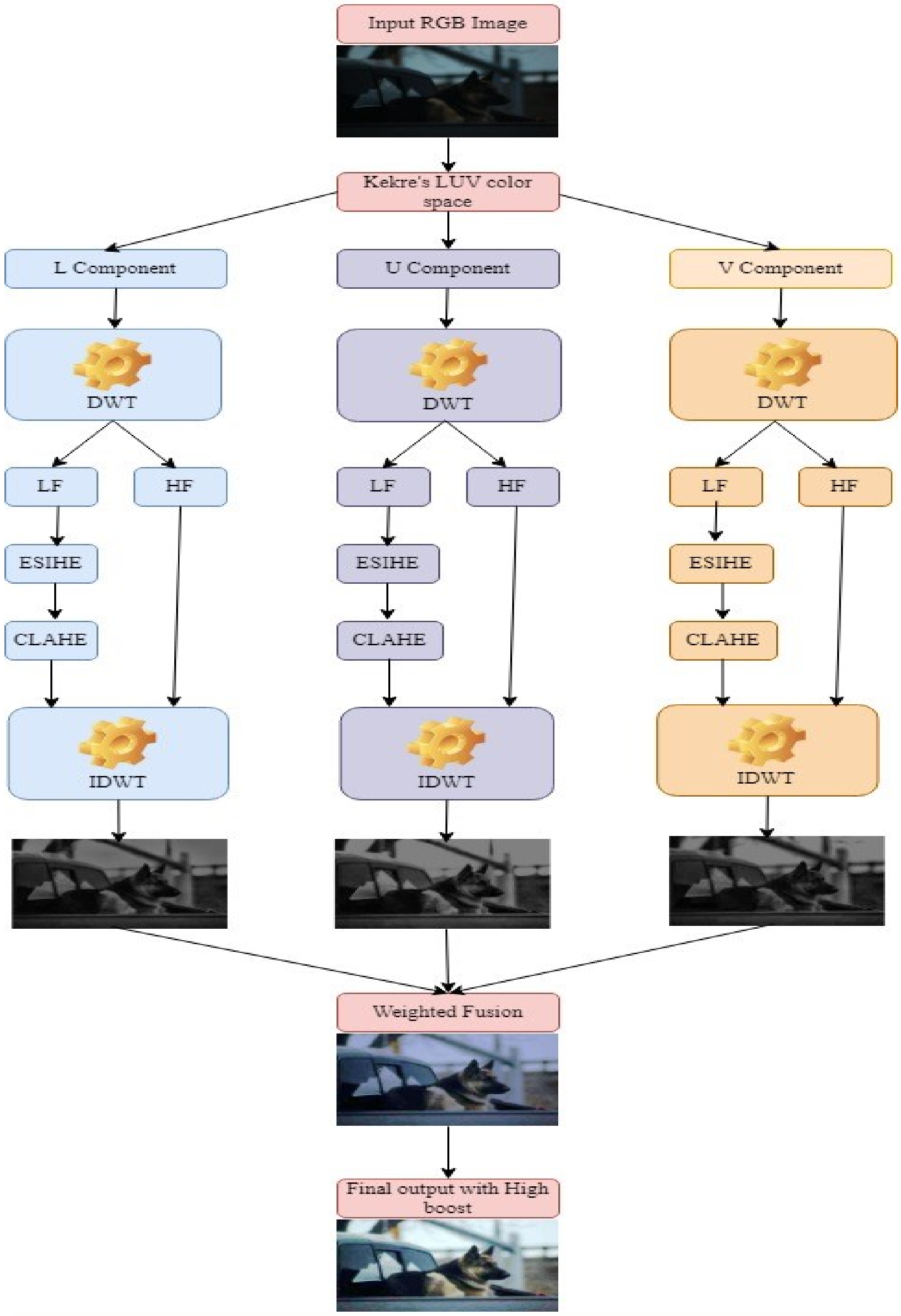


Figure 2. Flow chart of Proposed Method

- Combination of linear weights for recovered RGB image and histogram equalized image to balance the brightness in the resultant image

- To control the over-brightness, exposure and contrast limited techniques are applied on low-frequency components after decomposition by DWT

3. Methodology and Scope

In this part, a technique for enhancing non-uniform illumination photos to boost their quality is provided. Figure 2 depicts the proposed technique's framework and is explained in five sections. The first section details the conversion of RGB to Kekre's LUV color space & vice versa. The discrete wavelet transform and the inverted discrete wavelet transform are applied to the image, as explained in Section 2. Low light image enhancement algorithms used here, i.e., CLAHE & ESIHE, are enlightened in sections 3 and 4, respectively. The final part explains the weighted fusion to get enhanced output.

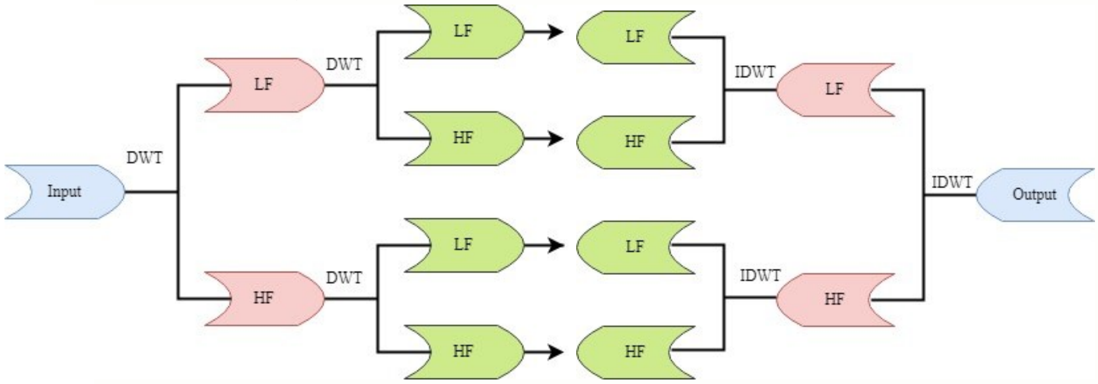


Figure 3. DWT and IDWT Flow diagrams

3.1 RGB to Kekre LUV Conversion

Initially, the low light RGB image is transformed into Kekre's LUV space. The vice versa transformation is as shown in equations 1 and 2. The poorly conditioned image is initially changed into luminance-chromaticity space. The following RGB to LUV conversion matrix shows a color image's L, U, and V components computed on corresponding R, G, and B components.

$$\begin{bmatrix} \boldsymbol{L} \\ \boldsymbol{U} \\ \boldsymbol{V} \end{bmatrix} = \begin{bmatrix} \mathbf{1} & \mathbf{1} & \mathbf{1} \\ \mathbf{-2} & \mathbf{1} & \mathbf{1} \\ \mathbf{0} & \mathbf{-1} & \mathbf{1} \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

The reverse can be achieved by the LUV to RGB conversion matrix as equation 2

$$\begin{bmatrix} \boldsymbol{R} \\ \boldsymbol{G} \\ \boldsymbol{B} \end{bmatrix} = \begin{bmatrix} \mathbf{1} & \mathbf{-2} & \mathbf{0} \\ \mathbf{1} & \mathbf{1} & \mathbf{-1} \\ \mathbf{1} & \mathbf{1} & \mathbf{1} \end{bmatrix} \begin{bmatrix} L \\ U \\ V \end{bmatrix} \quad (2)$$

3.2 DWT & IDWT

L, U, and V components obtained as an output from equation 1 undergo wavelet transformation as shown in figure 3, to decompose into low and high-frequency coefficients. When two-dimensional denoising signals, such as images and wavelets, are frequently used, selecting a wavelet type and level N of decomposition is the initial step. Here, decomposition is accomplished using the Haar wavelet. The two-dimensional image is transformed into wavelets using these wavelets. Determining threshold values for each level from 1 to N comes after the image file has been broken down. Reconstructing the image from the updated levels is the last stage, where an inverse wavelet transform is used, as shown in Figure 3.

3.3 ESIHE

The exposure-based sub-image histogram equalization method is used to improve the decomposed low-frequency component, as is explained in this section. The whole dynamic range is not used in photos with poor contrast. Images with low-intensity exposure have histogram bins concentrated toward the darker grey levels, whereas those with high-intensity exposure have histogram bins concentrated toward the brighter part. The categories of underexposed and overexposed photos can be broadly categorized based on this intensity exposure.

The ESIHE algorithm is displayed here. Three steps comprise the algorithm: choosing the exposure threshold, clipping the histogram, and subdivision and equalization. The following subsection detailed each step

Step 1: Calculate the image's histogram $h(k)$.

Step 2: Calculate exposure and threshold parameter X_a

$$exp = \frac{1}{L}\frac{\sum_{k-1}^{L} h(k)k}{\sum_{k-1}^{L} h(k)} \qquad (3)$$

Here L represents the total amount of grey levels, and the histogram is denoted by $h(k)$

The exposure-related parameter X_a provides the grey level value of the barrier that acts as a separator to divide the image into underexposed and overexposed sub-images.

$$X_a = L(1 - exp) \qquad (4)$$

Depending on whether the exposure value is less than or more than 0.5 for a picture with a dynamic range of 0 to L, this parameter can reach values higher or less than L/2 (grey level).

Step 3: Computation of the clipping threshold T_c and clip $h_c(k)$, the histogram

$$T_c = \frac{1}{L}\sum_{k=1}^{L} h(k) \qquad (5)$$

For $h(k) \geq T_c$ $\qquad h_c(k) = T_c$

where $h(k)$ and $h_c(k)$ indicate the original and clipped histogram, respectively.

Step 4: Utilizing the threshold setting X_a, split the clipped histogram into two sub-parts to obtain the underexposed and overexposed regions.

Step 5: Individual sub-histograms should be subjected to histogram equalization.

Step 6: Combination of these sub-parts in a single image for analysis.

Compared to other approaches, the ESIHE method produces images with excellent contrast enhancement and control over over-enhancing, making it a viable alternative for under-exposed images.

3.4 CLAHE

The output of the previous step is again equalized using CLAHE, which improves the local details. The implementation of CLAHE is given in the following steps

Step 1: Separates the original intensity image into contextual parts that don't overlap. MxN is the same as the total number of image tiles.

Step 2: Histogram of every region calculated using the current grey levels.

Step 3: computation of the limited contrast histogram (CL) value

$$N_{Avg} = \frac{(N_r X * N_r Y)}{N_{gray}} \qquad (6)$$

Here N_{Avg} stands for the average pixels, and N_{gray} stands for the number of grey levels. The values represent the region's X and Y dimensions $N_r X$ and $N_r Y$ respectively. CL can then be calculated as

$$N_{CL} = N_{clip} * N_{avg} \qquad (7)$$

where N_{CL} stands for actual CL and N_{clip} stands for normalized CL occupying the range from 0 to 1. Pixels having higher intensity than N_{CL} is clipped, and the notation shows the clipped pixels N_{clip}. Now, each grey level's average remaining pixel is calculated using the formula

$$N_{avggray} = N_{clip} \,/\, N_{gray} \qquad (8)$$

Histogram clipping can be carried out according to certain conditions, such as (1) clipping to value CL for higher values than CL. (2) The pixel value equals CL again if pixel intensity + $N_{avggray}$ is larger compared to CL; again, the pixel value equals CL. (3) for the cropped histogram original intensity + CL value.

Step 4: Redistribution of the leftover pixels throughout the intensity range

Step 5: New pixel assignments for grey levels should be calculated.

Step 6: The CLAHE (Y) output then undergoes color restoration steps as applied to gray images suggested in (Abdullah & Kabir, 2007).

After clipping the histogram portion above a threshold, the CLAHE algorithm reallocates the clipped pixels against every grey level. This procedure can somewhat reduce the noise enhancement problem. For some uses, the noise is still intolerable. Additionally, due to over-enhancing, it can lose some of the details in some areas of the supplied image.

Modified low- and high-frequency components are subjected to the inverse wavelet transform.

3.5 Wavelet Fusion

Output from the above step is fused linearly with traditional histogram equalization having weights as 0.7 and 0.3, respectively, as shown in equation 9, followed by a high boost algorithm to preserve edges in output enhanced image.

$$Output_{fused} = 0.7 * Output_1 + 0.3 * Output_2 \quad (9)$$

In the equation above, a small weight is in m multiplication with the HE output to reduce the impact distortion in color.

4. Result and Discussion

The experimental outcomes of CLAHE, ESIHE, the existing method, and the proposed technique are elaborated in the current section. The experimentation is done on three separate datasets containing different low-light photos. The ExDark, LoLi, and DPED datasets were used in this study. No-reference image quality

Evaluator (NIQE), and Blind/Reference Image Spatial Quality Evaluator (BRISQUE). Here the higher entropy score implies a better image quality. NIQE and BRISQUE are other no-reference image quality evaluators. A lesser NIQE or BRISQUE score implies a better enhancement.

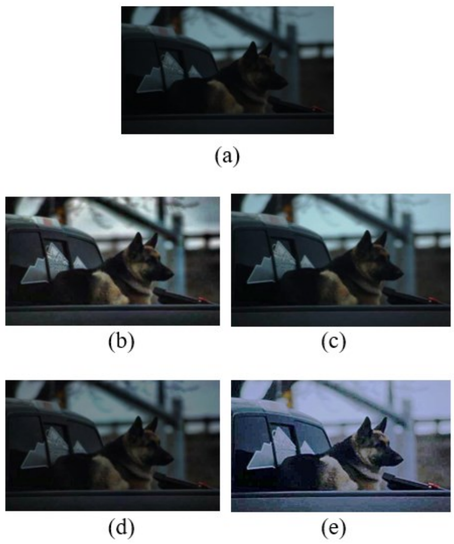


Figure 4. (a) Original low light image from ExDark Dataset. Result of (b) CLAHE (Mohan & Simon, 2020) (c) ESIHE (Singh & Kapoor, 2014) (d) CLAHE-DWT (Lidong & Wei, 2015) (e) Proposed Method

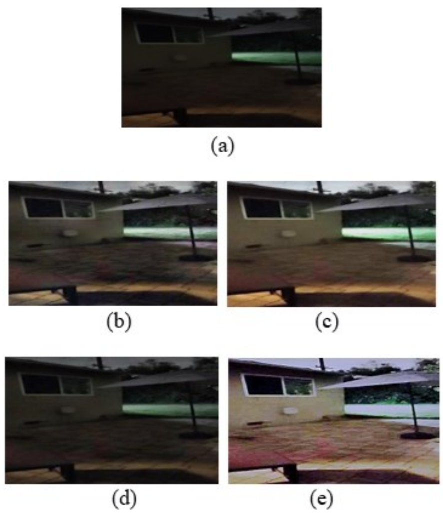


Figure 5. (a) Original low light image from LoLi Dataset. Result of (b) CLAHE (Mohan & Simon, 2020) (c) ESIHE (Singh & Kapoor, 2014) (d) CLAHE-DWT (Lidong & Wei, 2015) (e) Proposed Method

Figure 6. (a) Original low light image from DPED Dataset. Result of (b) CLAHE (Mohan & Simon, 2020) (c) ESIHE (Singh & Kapoor, 2014) (d) CLAHE-DWT (Lidong & Wei, 2015) (e) Proposed Method

The comparison results of low-light photos for various techniques are shown in Figures 4, 5, and 6. It implies that the proposed method reduces over-enhancing and color distortion compared to earlier methods while significantly improving low-light image enhancement. **Tables 1** through **9** quantitatively display findings from various methodologies.

Tables 1, 2, and **3** highlight the average Entropy, NIQE, and BRISQUE scores of different dark images experimented with over the ExDark dataset. It is perceived that the estimated method of enhancing poorly illuminated images using wavelet transform gives the highest score for Entropy, implying better enhancement results compared to other methods. Concerning the NIQE score, the suggested method ranked second highest after the existing method. The BRISQUE score is the lowest for the proposed method, indicating the best enhancement results.

The experimental outcomes from tables 4, 5, and 6 depict the evaluation of the LoLi dataset. Notably, the proposed algorithm achieves the highest scores among all methods evaluated by both Entropy and BRISQUE quality evaluators. These findings substantiate the efficacy of the proposed algorithm in enhancing results, outperforming existing methods significantly.

Table 1. Average Entropy Score of ExDark Dataset

Image	CLAHE (Mohan & Simon, 2020)	ESIHE (Singh & Kapoor, 2014)	CLAHE-DWT (Lidong & Wei, 2015)	Proposed
Bicycle	5.9	5.3	5.6	6.5
Boat	6.9	6.5	6.6	7.2
Bottle	5.6	4.9	5.3	6.5
Bus	5.7	5.0	5.5	6.6
Car	5.1	4.5	4.8	6.2
Cat	5.8	5.0	5.4	6.6
Chair	5.2	4.6	5.0	6.2
Cup	6.2	5.5	5.9	6.9
Dog	5.6	4.9	5.3	6.5
Motorbike	6.2	5.8	6.0	6.9
People	4.7	4.3	4.6	5.5
Table	5.6	5.0	5.3	6.7
Average	**5.7**	**5.1**	**5.4**	**6.5**

Table 2. Average NIQE Score of ExDark Dataset

Image	CLAHE (Mohan & Simon, 2020)	ESIHE (Singh & Kapoor, 2014)	CLAHE-DWT (Lidong & Wei, 2015)	Proposed
Bicycle	5.4	5.5	5.0	5.0
Boat	4.5	4.9	4.4	4.5
Bottle	4.8	5.5	4.8	4.9
Bus	4.8	5.1	4.7	4.8
Car	5.1	5.7	5.2	5.4
Cat	4.4	4.6	4.3	4.2
Chair	5.7	6.5	5.5	5.8
Cup	4.0	4.4	4.0	4.0
Dog	4.8	5.2	4.8	4.8
Motorbike	4.7	5.3	4.6	4.8
People	5.3	5.5	5.1	5.1
Table	5.1	6.1	5.2	5.9
Average	**4.9**	**5.3**	**4.8**	**4.9**

Table 3. Average BRISQUE Score of ExDark Dataset

Image	CLAHE (Mohan & Simon, 2020)	ESIHE (Singh & Kapoor, 2014)	CLAHE-DWT (Lidong & Wei, 2015)	Proposed
Bicycle	36.0	36.1	37.4	34.5
Boat	27.2	32.2	30.9	28.4
Bottle	39.0	42.5	41.0	30.6
Bus	37.2	40.9	40.0	30.9
Car	38.4	42.9	40.0	37.8
Cat	39.5	42.4	41.4	33.4
Chair	40.9	41.6	40.5	36.2
Cup	39.2	43.1	42.2	31.7
Dog	41.8	44.3	41.5	36.4
Motorbike	37.1	33.7	36.0	29.9
People	41.9	44.2	42.2	37.6
Table	40.3	44.7	40.8	35.8
Average	**38.2**	**40.7**	**39.5**	**33.6**

Table 4. Average Entropy Score of LoLi Dataset

Image	CLAHE (Mohan & Simon, 2020)	ESIHE (Singh & Kapoor, 2014)	CLAHE-DWT (Lidong & Wei, 2015)	Proposed
Huawei	6.2	5.2	5.7	7.3
LG	6.5	5.2	5.8	7.6
Oneplus	5.2	4.1	4.6	7.3
Oppo	7.3	6.4	6.7	7.6
Pixel	7.6	6.9	7.1	7.7
Vivo	6.2	5.1	5.6	7.3
Xiaomi	5.8	4.4	5.1	7.2
iPhone	6.4	5.6	5.9	7.3
Average	**6.4**	**5.4**	**5.8**	**7.4**

Table 5. Average NIQE Score of LoLi Dataset

Image	CLAHE (Mohan & Simon, 2020)	ESIHE (Singh & Kapoor, 2014)	CLAHE-DWT (Lidong & Wei, 2015)	Proposed
Huawei	4.0	4.4	4.5	5.3
LG	3.6	4.3	3.8	4.5
Oneplus	8.4	9.7	8.4	9.2
Oppo	3.5	3.8	3.4	4.9
Pixel	3.1	3.0	2.9	3.7
Vivo	4.9	5.4	5.0	6.6
Xiaomi	4.5	5.7	5.1	6.3
iPhone	3.9	4.1	4.0	4.9
Average	**4.5**	**5.1**	**4.6**	**5.7**

Table 6. Average BRISQUE Score of LoLi Dataset

Image	CLAHE (Mohan & Simon, 2020)	ESIHE (Singh & Kapoor, 2014)	CLAHE-DWT (Lidong & Wei, 2015)	Proposed
Huawei	37.4	39.9	41.7	31.7
LG	36.8	41.0	41.8	38.1
Oneplus	51.0	57.5	48.3	46.5
Oppo	28.4	32.6	32.8	20.8
Pixel	24.8	27.6	28.1	17.3
Vivo	40.1	43.0	42.4	41.1
Xiaomi	42.6	47.4	42.7	38.5
iPhone	33.1	33.9	36.4	29.7
Average	**36.8**	**40.4**	**39.3**	**33.0**

Table 7. Average Entropy Score of DPED Dataset

Image	CLAHE (Mohan & Simon, 2020)	ESIHE (Singh & Kapoor, 2014)	CLAHE-DWT (Lidong & Wei, 2015)	Proposed
Blackberry	7.7	7.6	7.4	7.6
Canon	7.5	7.3	7.1	7.5
iPhone	7.6	7.1	7.0	7.6
Sony	7.8	7.6	7.4	7.7
Average	**7.6**	**7.4**	**7.2**	**7.6**

Table 8. Average NIQE Score of DPED Dataset

Image	CLAHE (Mohan & Simon, 2020)	ESIHE (Singh & Kapoor, 2014)	CLAHE-DWT (Lidong & Wei, 2015)	Proposed
Blackberry	4.0	3.4	3.6	5.0
Canon	3.3	2.9	3.3	4.4
iPhone	2.7	2.9	2.5	4.1
Sony	3.5	3.0	3.1	4.5
Average	**3.4**	**3.0**	**3.1**	**4.5**

Table 9. Average BRISQUE Score of DPED Dataset

Image	CLAHE (Mohan & Simon, 2020)	ESIHE (Singh & Kapoor, 2014)	CLAHE-DWT (Li-dong & Wei, 2015)	Proposed
Blackberry	30.4	26.5	24.0	22.1
Canon	21.2	27.5	28.5	22.3
iPhone	21.1	28.6	26.4	19.0
Sony	20.4	21.4	26.4	19.9
Average	**23.3**	**26.0**	**26.3**	**20.8**

Tables 7, 8, and **9** highlight the performance evaluation of techniques on the DPED dataset. Significantly, the recommended technique demonstrates impressive results, boasting high scores for Entropy while recording the lowest BRISQUE score among the experimented methods. This underscores the effectiveness of the recommended technique in optimizing results on the DPED dataset.

By giving less weight to the HE output and more weight to the output of the proposed method, the over-enhancement effect in output can be reduced to a moderate level due to the linear fusion used in the proposed method.

5. Conclusion

It is crucial but challenging for photographs with poor lighting to improve the contrast and restore the details. Poor lighting circumstances and factors, including light absorption, reflection, bending, and scattering, result in dimness and distortion; such images may lose contrast and degrade. It's possible that the current algorithms for picture enhancement can't effectively boost contrast and restore color for low-light photographs. As a result, this paper, the wavelet-based algorithm for enhanced fusion has five main steps: conversion of RGB to LUV color spaces, decomposition of each component using wavelet transform, applying ESIHE to get an exposure-based enhancement of dark and bright regions separately, applying CLAHE to control over bright regions, and weighted fusion with traditional HE method followed by edge preservation.

The proposed algorithm can efficiently accomplish contrast enrichment based on experimentations performed on various datasets having differently captured categories of poorly illuminated images against different evaluation parameters such as Entropy, NIQE, and BRISQUE. The method outperforms existing enhancement algorithms in visual performance and quantitative evaluation by giving a higher Entropy score and a lower BRISQUE score across three different datasets.

6. Limitations and future research

With the experiments performed on different datasets having a variety of low-light images, noise is observed in a few patches, affecting the NIQE score. As a corrective measure, the proposed method can be added with a noise amplification feature compared to the results of diverse fusion methodologies and contrast enhancement metrics. Further, similarly, the findings would be tested by combining the output from other local and global methods. Our goal is to construct a quantifiable assessment of the effectiveness of contrast-enhancement algorithms based on various measures described in the paper.

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