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Adapting to the Dark: A Novel Adaptive Low Light Illumination Correction Algorithm for Video Sequences in Wireless Communications

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ABSTRACT- The lower image quality and higher noise levels of low light images can have a substantial effect on wireless communication. Images typically have less brightness, less clarity, and more picture noise in low light situations. The precision and dependability of picture-based communication may be impacted by this decline in image quality. Low light levels can be detrimental to video chats since it becomes difficult for the camera to get clear pictures of the user's face. This may lead to decreased video quality, trouble with facial recognition, and a generally worse user experience when communicating over video. Low light illumination correction algorithms are frequently made to work quickly and effectively in order to enable real-time video-based wireless communication. Correcting uneven illumination or low light in images is crucial for various fields; as such images pose challenges for human recognition, computer vision algorithms, and multimedia algorithms. An adaptive illumination correction algorithm based on a simple log transformation approach enhanced by a hyperbolic beta transformation and a logarithmic image processing is presented in this research. It has an adaptive optimization function that adjusts itself based on the image's illumination and reflectance. Low computation and minimal parameter optimization are the hallmarks of this method. A variety of illuminated images and video sequences from various datasets are used to evaluate the suggested adaptive illumination approach. This adaptive illumination approach's experimental findings are impressive compared to those produced using prior techniques. The results reveal that the proposed system can adapt to various image-based communication and surveillance video sequences taken under various illumination conditions.

Keywords: Illumination correction; exponential function; hyperbolic tangent function; Log Transformation, wireless communications.

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1. INTRODUCTION

Illumination of an image property is the reason behind the high quality and better visual perceptual images. Images with proper and appropriate brightness help the real time video based wireless communication and computer vision algorithms detect and localize the objects accurately [1]. Low light illumination correction can improve the quality of images taken in difficult lighting circumstances for remote sensing applications like environmental monitoring or remote infrastructure inspections. This makes it possible to assess and make decisions based on the data that has been collected more effectively, allowing wireless transfer of crucial information. Images taken in low light often contain additional noise or artifacts, which might hinder wireless transmission. Noise can result in errors or packet loss, resulting in damaged images or communication flow disruptions. The camera's ability to capture a picture accurately in low light conditions may be hampered. As a result, the overall quality of wireless communication may suffer from poorer signal strength and reception. It is prevalent that during nighttime and low lighting conditions, most currently available digital acquisition devices are incapable of capturing good-quality photographs and are degraded by low perceptual quality [2]. Illumination variation is one of the prevalent problems that are often observed in many of the real-time video sequences that were captured with surveillance cameras and video based wireless communication. Low light illumination adjustment can help security cameras that are used in low light situations. The accuracy and dependability of security and surveillance systems over wireless networks are improved by these techniques by increasing the visibility of important elements like facial features or license plate numbers. Insufficient contrast in medical imaging modalities might impair the observer's capability to analyze the images, increasing processing complexity. This problem degrades the performance of object detection and tracking algorithms employed on such video sequences. The rapid change in the illumination occurs due to flashlights leading to overexposure, shadowing, and dim/dark lights leading to underexposure. In general, it is observed that variation of illumination is a crucial reason for the failure of detection and tracking algorithms. The image enhancement goal is to improve or restore image quality in terms of properties like luminosity contrast and color. While improving the quality, utmost care is taken to introduce no external effects. The recovered or enhanced images look better, similar, and suitable for image applications and processing. Therefore, it is advisable to utilize illumination correction algorithms prior to processing video frames for real-time video-based wireless communication applications, as well as for tracking and detection algorithms. The quality and transmission of low light images in wireless communication are frequently improved by manufacturers and developers using a variety of approaches, image enhancement algorithms, noise reduction filters, and adaptive compression methods.

Logarithmic image processing and a hyperbolic beta transformation are used to create an adaptive illumination correction technique in this work. The Proposed adaptive method considers the LIP model's fundamental idea and integrates with an adaptive parameter adjustment strategy based on the input image intensities in an iterative manner. With this iterative model, the parameters are adjusted adaptively based on the input intensities resulting in a high-quality illumination-corrected image. There are six parts to this article. Section one introduces the issue and highlights the current research need and scope. Section two reviews previous relevant work, emphasizing the flaws and strengths. Section three discusses the log transformation model and its usefulness for image improvement. The proposed method was discussed in section four, and the experimental results were explained in section five, along with a comparison to traditional techniques. Section six discusses the conclusions and observations.

2. LITERATURE REVIEW

Numerous algorithms were proposed in the literature; however, this section presents a few of them related to the present context of work. Hsueh.et al. [3] proposed Illumination Adaptive Video Coding Scheme for In-vehicle Video Applications which combines the advantages of the single-scale Retinex (SSR) and the weighted histogram separation (WHS). Linet et al. [4] and others developed an improved multi-scale retinex algorithm (IMSR) by replacing the log transformation used in the conventional multi-scale retinex approach. Instead, a sigmoid function is used to lessen the loss of image data.

Ying et al. [5] suggested a camera response model-based algorithm that considers the impact of the camera response function in the development of image enhancement. The camera response was used to calculate the exposure ratio map using histogram characteristics in this algorithm. Later the identified response is used to improve the input degraded picture. A sequential decomposition-based approach was proposed by Ren et al. [6], which works by decomposing the retinex model into a successive sequence to approximate a condensed noise reflectance and a piecewise illumination. Later the illumination layer is modified with a specialized method and smoothed using weighting matrices.

In [7], Mahmoud et al. presented a method for color constancy using deep networks. They used deep networks to estimate the illuminant color changes and gamma correction for the extracted semantic regions. From the results, it was observed that this approach yielded an improvement of 40% when compared with traditional retinex algorithms. In another approach, Wang et al. [8] have deployed the concept of a deep network for estimating illumination correction, for which they have designed 11 convolutional layer structure and included the global averaging pooling concept. It was observed that this approach had reduced 60% of the average angular error.

Murugan.et al. [9] presented Object Detection Based Modified Yolo Algorithm in Wireless Communication where the author used low-pass filter and unsharp filter to reduce noise and improve the sharpness of the image. A fast and effective low-illumination video enhancement algorithm was proposed by Hu. Y. et al. [10]. This approach combined the retinex theory with the dark channel prior theory to get better contrast and reduce the noise of poor illumination videos. Considering enhancing low illumination videos and amplifying noise at once, noise reduction before enhancement improves video enhancement effects. As a result, the author combines the benefits of guided and median filtering to develop a more comprehensive denoising algorithm, which would be applied to YCbCr space. Later, estimated luminance transmission maps in HSI space are performed, and the atmospheric model is used to recover the low illumination video. It was observed in the survey that illumination variation is degrading the performance of object detection and tracking, and an adaptive, more straightforward approach has to be employed in order to attain constant illumination of video sequences or images.

Que.Y.et.al [11] developed an algorithm by considering the exposure level quantity of the input pictures local and global luminance components and introduced a designed multiscale edge-preserving smoothing (MEPS) model for straightly representing the weight maps. However, the method is not very robust to dissimilar image characteristics.

The above literature review observed that many of these methods suffer from edging outliers when the image is enhanced. Due to this process, the edge details in the image are lost; secondly, the processing time is a crucial parameter in validating an effective enhancement method. Some methods also lead to video flickering artifacts due to uneven illumination correction, and the video sequences' smooth continuity will be lost.

3. LOG TRANSFORMATION MODEL FOR IMAGE ENHANCEMENT

3.1 Modified log transform and its impact on illumination

The primary goal of this work is to improve the visibility and perceptibility of video frames or images that are taken in low light and with irregular exposure times. Noisy images with erratic spatial distributions are a common occurrence in these photographs. Improving a low-light image or video frame generally boosts low and middle-level intensity while minimizing high-level intensity. When adjusting or updating

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low-intensity values, care must be taken to ensure that the noisy aspects are not magnified. The image contrast levels must be improved locally rather than globally, yet a global intensity balance is recommended.

Usually, the pixel values of images or video frames acquired in low-light scenarios are characterized by very low dynamic ranges that are not similar to those of sensing and display devices. So, it is recommended to normalize these values initially to utilize the full dynamic range. For many of the images, it is appropriate to scale the pixels linearly to fall in the range of [0 1] by transforming them with the subsequent *equation(1)*.

$$L_0(i) = \frac{L_i(k) - \min(L_i(k))}{[\max(L_i(k)) - \min\,(L_i(k))]} \quad (1)$$

In the above *equation (1)*, the term $L_0(i)$ is the output resultant normalized frame [12], which relies on input $L_i(k)$ intensities. The higher intensities will be minimized by employing the log transformation for the normalized values using the following *equation (2)*.

$$L_1(i) = \frac{\max(L_0(i))}{\log(\max(L_0(i))+1)} \log(L_0(i) + 1) \quad (2)$$

The above function approximates the transformation performed by the retina of the human visual system. This type of transformation enlarges dim pixels' values while minimizing the image's higher intensity levels [13]. To further modify the above equation, a non-linear exponential mapping function adjusts the local contrast values and attenuates the higher intensities.

Chen and others [14] have presented a non-linear mapping increasing function defined as *equation (3)* mentioned while describing Finsler metric calculation. So, this non-linear mapping function can be adopted for intensity suppression where $T(x)$ is the transformed output of x input value.

$$T(x) = 1 - \exp(-x) \quad (3)$$

3.2 Logarithmic Image Processing (LIP)

Earlier LIP models were constructed with the equation of light passing through the filters. Lim's classical LIP model has several limitations, like higher range run over due to mathematical properties that deal with the model. So, the parametric extension of this model was proposed by several authors [15] [16] [17] [18]. Many of these provide more flexibility with numerous applications. Based on this, several LIP models exist to integrate multiple image characteristics; however, the LIP mathematical analysis provided in [15] is employed in this context. Accordingly, some of the basic operations with the LIP model of image processing include.

$$\text{Isomorphism: } \emptyset_p(x) = \frac{1}{2}\log\left(\frac{1+x}{1-x}\right) \quad (4)$$

$$\text{Addition: } \emptyset_p(x) = \frac{u+v}{1+uv} \quad (5)$$

$$\text{Multiplication: } \emptyset_p(x) = \frac{(1+u)^{\alpha} - (1-u)^{\alpha}}{(1+u)^{\alpha} + (1-u)^{\alpha}} \quad (6)$$

To attain the above LIP models' most satisfactory performance, it is adapted to fit the nature of the pictures used.

4. PROPOSED ILLUMINATION CORRECTION METHOD

The main objective of the proposed adaptive illumination correction method is to recuperate acceptable video quality of video sequences acquired under varying illumination for wireless communication application. The method considers the LIP model's fundamental idea and integrates it with the proposed adaptive adjustable and updating parameter lambda. The strategy is based on altering the parameter in accordance with the input image intensities in an iterative manner by controlling the iteration process using the blind depth quality metric BDQM [19].

The fundamental idea of illumination enhancement is derived from [20], where the authors have employed a controlling parameter lambda (λ) that is varied in an interval of [2 7], which is practically not feasible when the input illumination is varying and unknown. Hence, this article proposes an adaptive iterative process to update the lambda parameter based on the input image illuminance, measured with a quality metric. The main contribution of this paper relies on proposing a modified LIP model with adaptively adjustable regularizing parameter lambda in accordance with the changes in image illumination. The entire flow process to update the control parameter is presented in the following flow chart shown in *figure 3*, and the steps involved in the process are described below with output of images at each stage by considering a single image.

Step1**:** Let the original input image pixel values be represented as '*X*'. These values are initially transformed using *equation (1)*, and then the resultant transformed image I_1 can be represented as stated in *equation (7)*. The higher intensities of image *X* will be minimized.

$$I_1 = \frac{\max\,(X)}{\log\,(\max(X)+1)} * \log\,(X + 1) \quad (7)$$

Figure 1. (a) Original Image (I) (b) Output Image

Step2**:** The same input values are modified with an exponential function such that the local contrast values are preserved while attenuating the higher intensity values. This can be achieved by *equation (8)* to obtain the resultant image I_2.

$$I_2 = (1 - \exp(-X)) \quad (8)$$

Figure 2. *(a)* Original Image (I) *(b)* Output Image after step 2 (I2)

Step 3: The above two images I1 and I2 are combined with the proper LIP model. In this work, we have adopted the addition of two pictures, as stated in *equation 9*. So, the transformed image I3 can be obtained as indicated in *figure 4*.

$$I_3 = \frac{I_1+I_2}{1+(I_1*I_2)} \tag{9}$$

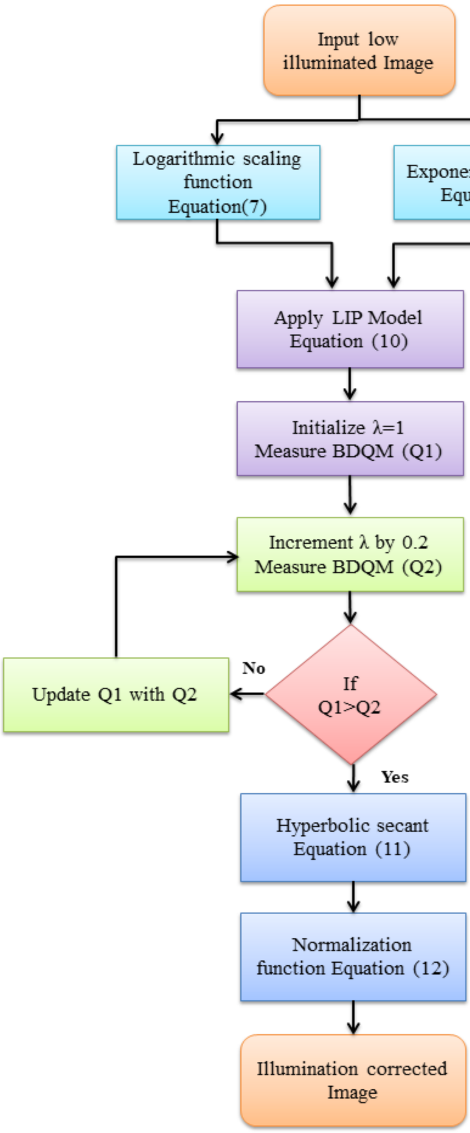


Figure 3. Flow chart of the proposed illumination correction model

Figure 4. shows the output image I3

Step 4: To achieve the best performance of the above equation and adapt to any nature of images, the above equation is modified as

$$I_3 = \frac{I_1+I_2}{\lambda+(I_1*I_2)} \tag{10}$$

In the above *equation (10)*, the parameter 'λ' controls the enhancement process, and hence it is included so that unsuitable pixel generation can be avoided. However, selecting the parameter is questionable, and therefore, a suitable adaptive approach must be employed to fit this problem. In this work, the selection of 'λ' parameter is made adaptively based on BDQM estimation.

4.1 Updating Process for 'λ' parameter

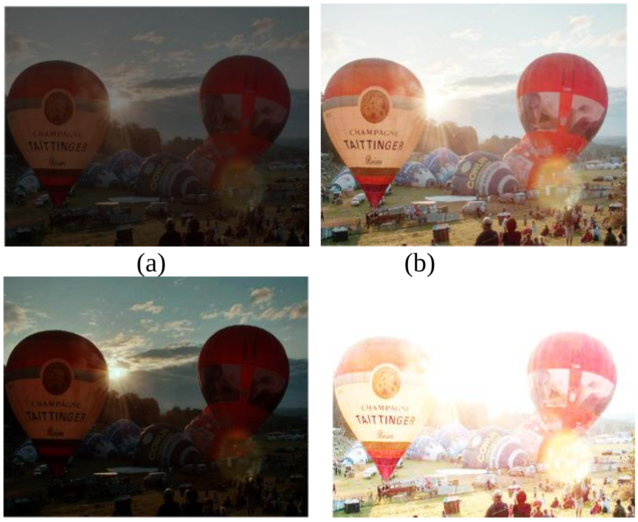
Step a: compute I_3 with λ=1 and compute BDQM, store it as q_1.

Step b: increment the value of λ by 0.2 and compute I_3 again, and BDQM of it is stored as q_2.

Step c: if $q_1>q_2$, then stop the iteration if not, go to *step (a)* and continue the iterative process till the end of the total range of values and consider the outcome as I_3.

4.2 Impact of adaptive lambda correction

The impact of lambda correction is illustrated in the following *figure 5* using a different image.



(a) (b)

(c) (d)

Figure 5. Impact of adaptive lambda correction

In *figure 5*, the impact of the proposed approach of adaptive adjustment of lambda is shown in *fig. 5(a)* is the Original Input image with Blind/Reference less Image Spatial Quality Evaluator BRISQUE [21] = 28.29,*fig. 5(b)* is the Proposed output with BRISQUE =16.40, *fig. (c)* is the output of [19] with lambda = 2, BRISQUE=18.76, *fig. (d)* is the output of [19] with lambda = 5, BRISQUE=33.45. It can be observed that it becomes cumbersome to select the value of lambda.

Figure 5(c) shows that when the lambda value is low, the image is not enhanced; however, when the lambda is higher, the image is over-enhanced, as shown in *figure 5(d).* Both cases are not suitable for recognition and analysis. The proposed adaptive adjustment effectiveness is shown in *figure 5(b)*, which has a lower BRISQUE score than the input image and high perceptibility.

After obtaining the outcome of I_3, the further image proceeds for enhancement. Since it is observed that despite the overall additive brightness of image I_3, the image I_3 still lacks brighter values; hence, it is recommended to process it further for proper appearance.

Step 5: To accomplish this, a modified cumulative distribution function (CDF) of hyperbolic secant distribution [22] is employed to recover the overall brightness. This is one type of S-curve that aims to correct the illumination and contrast values of the image. So, the above image obtained with *equation (10)*, termed I_3 can be transformed as

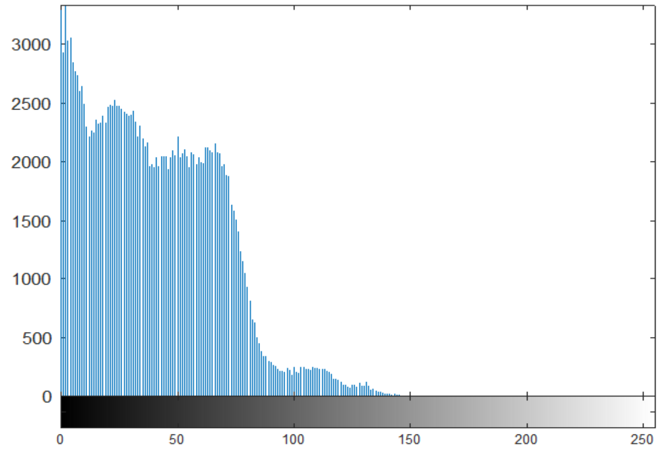
$$I_4 = \mathrm{erf}(\ \lambda * atan(exp(I_3)) - 0.5 * I_3) \qquad (11)$$

In the above equation, the term 'λ' is the finalized value obtained after the iterative process, and I_3 is its respective enhanced image with that value. The moderation has aided in improving the function processing efficiency in terms of brightness enhancement.

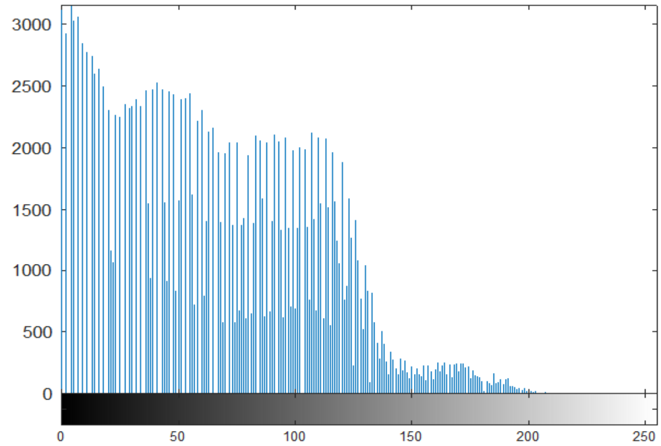
Step 6: In the above *equation (11)*, the error function is included to increase the curvy transformation of hyperbolic secant distribution, which is very beneficial in improving the darker pixels' brightness. Besides, the value of *pi/2* is replaced with the term 'λ' to control the process of enhancement. Finally, normalization is employed to get the enhanced image I_5.

$$I_5 = \frac{I_4 - \min(I_4)}{\max(I_4) - \min(I_4)} \qquad (12)$$

(a) (b)



(c)



(d)

Figure 6. The proposed approach analysis (a) Original Input (I) Low Illumination Image (b) Enhanced (I_5) with proposed approach (c) Histogram of the original image (I) (d) Histogram of the enhanced Image (I_5)

Above, *figure 6* depicts the images and their histogram distribution. *Figure 2(a)* and *2(b)* shows the original input image and the processed image, and *figure 2(c)* and *2(d)* depicts their respective histogram distribution. In the processed image, the intensity levels are spread over the range, leading to an accurate change in the illumination without introducing any change in the original image content.

5. OUTCOMES AND SIGNIFICANCE

To evaluate the proposed adaptive illumination approach performance, multiple low-illumination images and video sequences are collected from [23][24][25][26]. The method is compared against four existing methods like Contrast Limited adaptive Histogram Equalization (CLAHE) [27], Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE) [28], Content adaptive Image detail Enhancement (CADE) [29] and Globally Guided Image Filtering (GGIF) [30] enhancement methods. The proposed enhancement approach performance assessment evaluated in terms of multiple metrics like Relative Contrast Error (RCE) [31], structural contrast-quality index (SCQI) [32], Peak Signal to Noise Ratio (PSNR) [33].

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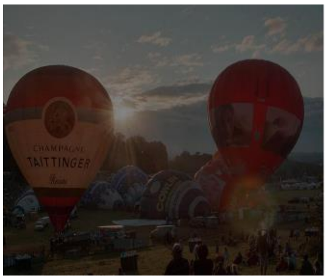
Image 1


Image 2


Image 3


Image 4


Image 5

Figure 7. Image Test Samples taken from different datasets.

5.1 Relative Contrast Error

Relative Contrast Error (RCE) [31] is a metric that is commonly used to evaluate the degree of contrast enhancement in image processing. The RCE metric allows for the quantification of the difference between the contrast levels of the original image and the enhanced image.

Table 1. Performance analysis of the proposed enhancement approach in terms of RCE

Parameter	Method	Image1	Image 2	Image 3	Image 4	Image 5	AVG
RCE[31]	**CLAHE[27]**	0.446	0.436	0.388	0.417	0.45	0.427
	BPDFHE[28]	0.465	0.489	0.487	0.498	0.503	0.488
	CADE[29]	0.441	0.496	0.495	0.498	0.502	0.486
	GGIF[30]	0.499	0.594	0.541	0.503	0.501	0.527
	Proposed Method	**0.35**	**0.409**	**0.424**	**0.365**	**0.442**	**0.398**

The analytical graph of the average RCE values in *figure 8*, which clearly shows that the proposed algorithm consistently outperformed the other methods. Additionally, *table 1* presents the RCE values obtained for each method, and it is strong that the proposed algorithm had the Lowest LOE among all the state-of-the-art methods, indicating its supremacy over the existing approaches.

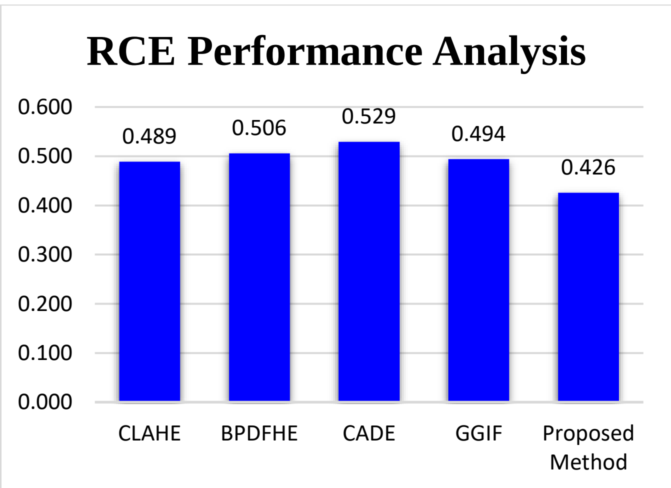

Figure 8. Performance analysis of RCE parameter

5.2 Structural Contrast Quality Index (SCQI)

The Structural Contrast Quality Index (SCQI) [32] is a measure that assesses the contrast quality of an image. It works by evaluating the definition and clarity of edges in an image and the contrast between neighboring regions. High-quality images should have well-defined edges and a clear distinction between adjacent regions.

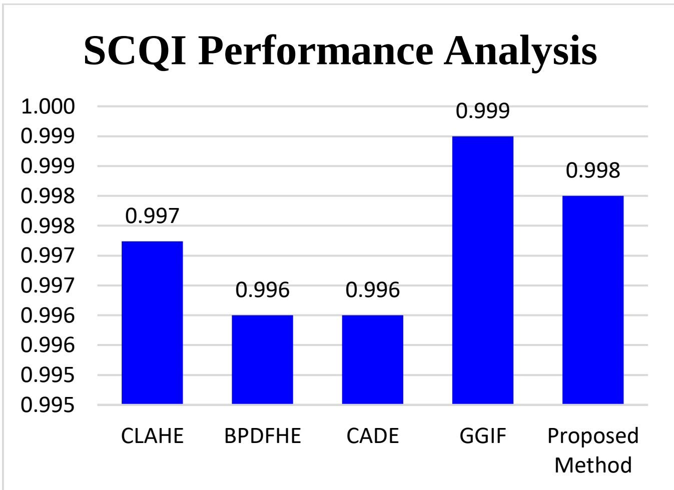

Figure 9. Performance analysis of SCQI parameter

Typically, the SCQI matrix is normalized to a range of 0 to 1. A score of 1 indicates excellent contrast quality, while 0 suggests poor contrast quality.

Table 2. Performance analysis of the proposed enhancement approach in terms of SCQI

Parameter	Method	Image1	Image 2	Image 3	Image 4	Image 5	AVG
SCQI[32]	**CLAHE[27]**	0.995	0.997	0.991	0.994	0.99	0.993
	BPDFHE[28]	**0.998**	**0.999**	**0.998**	0.993	0.99	0.995
	CADE[29]	**0.998**	**0.999**	**0.998**	0.991	0.99	0.995
	GGIF[30]	0.997	0.998	**0.998**	0.994	0.99	0.994
	Proposed Method	**0.998**	**0.999**	**0.998**	**0.995**	**0.99**	**0.996**

5.3 Peak signal to Noise Ratio (PSNR)

An improved image should ideally have a high PSNR [33] (Peak Signal-to-Noise Ratio) as compared to the original image. A high PSNR value suggests that the enhanced image is of greater quality or has less distortion than the original, and that less noise or error was added during the enhancement process.

Table 3. Performance analysis of the proposed enhancement approach in terms of PSNR

Parameter	Method	Image1	Image 2	Image 3	Image 4	Image 5	AVG
PSNR[33]	**CLAHE[27]**	13.87	16.974	12.362	16.007	25.425	16.928
	BPDFHE[28]	**24.342**	25.951	28.251	24.811	23.184	25.308
	CADE[29]	12.952	19.396	18.767	21.182	22.354	18.93
	GGIF[30]	18.002	23.628	24.239	**31.681**	**29.51**	25.412
	Proposed Method	23.32	**27.101**	**28.563**	24.262	25.005	**25.65**

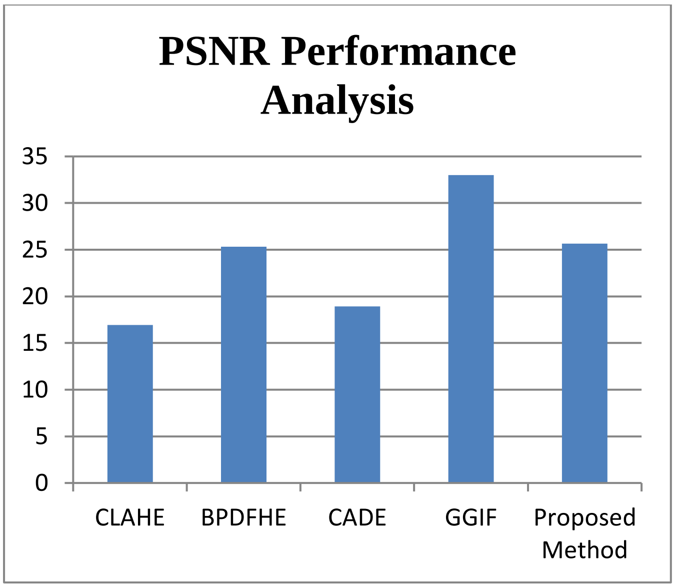

Figure 10. Performance analysis of PSNR parameter

The above *table 3* shows that the proposed images enhance method attain a high PSNR value compared to the State-art-methods.

The performance metrics are represented in *tables 1 to 3* and *figures 8 to 10*. The analysis observes that the proposed adaptive method retains superior values compared with the existing four methods. However, it can be observed that it gains with a smaller variation in some respects. In all aspects, the approach yielded considerable superior visual and metrical values with simple mathematical operations.

The proposed adaptive illumination correction method is suitable for enhancing very low and night-time acquired images and real time video sequences in wireless communication. Where the contrast values are altered without the intrusion of noise components observed in existing methods. The visual responses for the proposed approach are depicted in *figure 11*, where it can be observed that the approach could retain very dark or low illuminated images as shown in *a1 to a5* of *figure 11* to leverage details most effectively.

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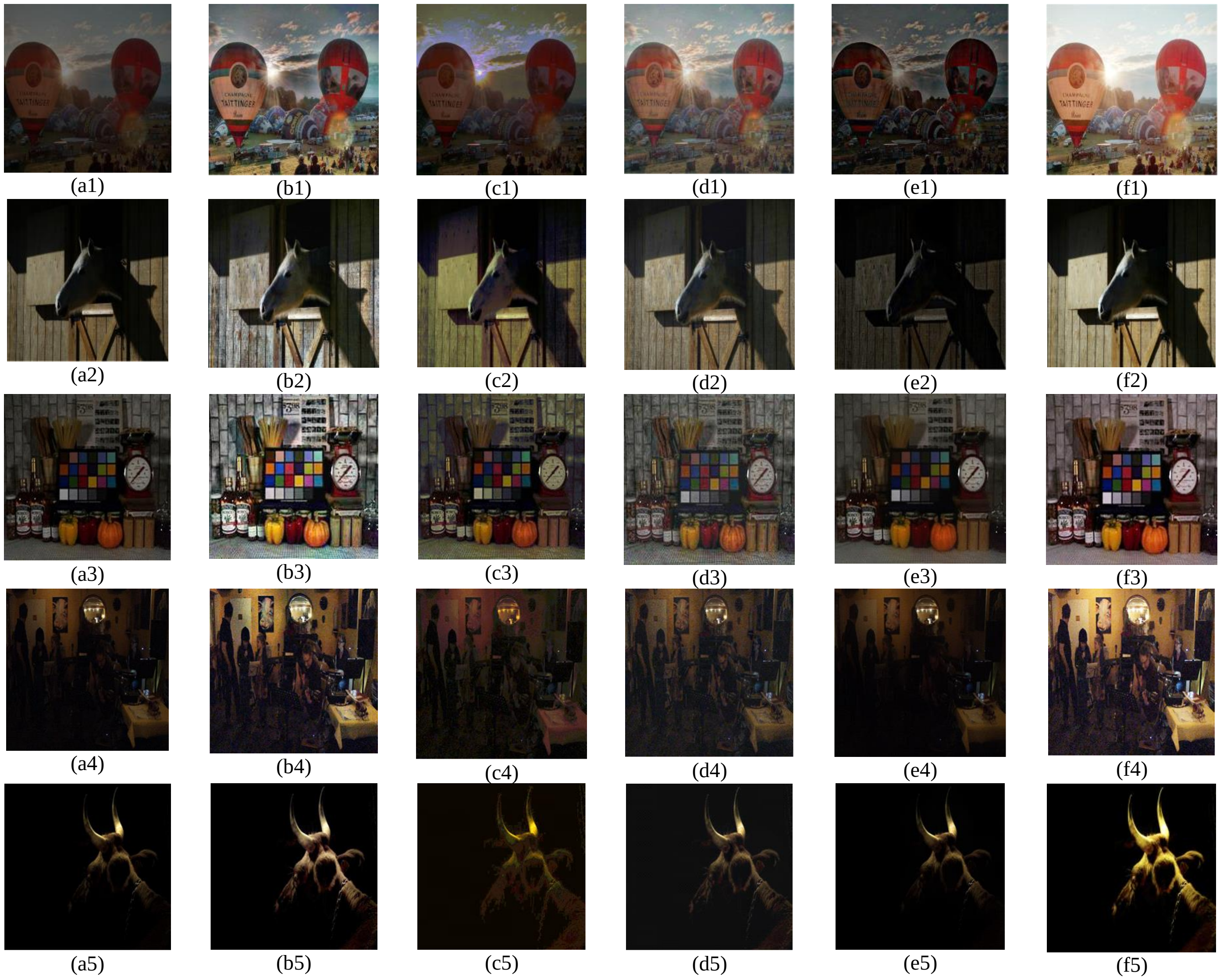

Figure 11. Visual Performance of the proposed approach (a1) - (a5): Original Input Images, (b1) - (b5) output with CLAHE, (c1) - (c5) output with BPDFHE, (d1) - (d5) output with CADE, (e1) - (e5) output with GGIF (f1)-f (5) with Proposed method.

6. CONCLUSION

This paper presents an improved version of the log transformation model of image enhancement by including a hyperbolic tangent transformation with the logarithm image processing model. The algorithm is tested and compared with state-of-the-art methods for multiple metrics and visual analysis. The approach was assessed and evaluated in terms of various metrics and compared with four existing methods, and it was observed that experimental results yielded superior results in all aspects. The analysis concludes that this approach is more suitable for low-illuminated, night-exposure images, medical images and video based wireless communication sequences that aim to be enhanced with high quality before transmission. Experimental results proved that the proposed algorithm improved the processed image details and enhanced the overall visual quality. Moreover, the proposed method is robust to different image characteristics and computationally efficient. Thus, it is qualified for real applications. However, this method also suffers from instability for a few images where the condition of break point does not converge, leading to more processing time. So, in future, this work may be carried out further in dealing with this limitation and employ supervised algorithms for improving the metrics.

Author Contributions: Chinthakindi Kiran Kumar conceived and designed the study, collected, and analyzed the data, and wrote the manuscript. Dr Kirti Rawal provided critical feedback on the study design, contributed to data interpretation, and revised the manuscript. Dr Gaurav Sethi contributed to the study design and data interpretation, and reviewed and edited the manuscript for intellectual content. All authors approved the final version of the manuscript for submission.

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