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Modified Effective Histogram Equalization method for Night Time Color image enhancement with Energy Curve

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ABSTRACT

By modifying brightness, contrast, sharpness, and color balance, color photographs can be made more visually appealing. By highlighting significant characteristics and reducing noise or distortion, the main aim of enhancement is to make the image more aesthetically visible, lucid, and interpretable. Techniques vary from basic brightness and contrast tweaks to sophisticated algorithms. Improved quality in low-light video is vital for distinguishing individuals and activities in security and surveillance. Challenges like noise amplification and over-enhancement can create unnatural images with exaggerated features. This paper addresses these issues by introducing the Exposure-Based Sub Histogram Equalization (ESIHE) method that uses an Energy Curve to enhance low-exposure or night color images effectively, which is similar to a histogram and based on the spatial contextual information of an image. To enhance outcomes, the suggested approach, ESIHE_Energy, combines an Energy Curve and Exposure-based Sub-image Histogram Equalization with spatial contextual information. The evaluation of the proposed approach was conducted on multiple datasets consisting of night-time color images. Its performance was benchmarked against several established methods, including Histogram Equalization (HE), Brightness Preserving Bi-Histogram Equalization (BBHE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Dynamic Stochastic Histogram Equalization (DSHE), Recursive ESIHE (R-ESIHE), Recursive Symmetric ESIHE (RS-ESIHE), and ESIHE. Various image quality metrics, such as Peak PSNR, MSE, Entropy, Structural Similarity Index (SSIM), and Feature Similarity Index (FSIM), were utilized for comparison. The method yielded an average PSNR of 16.336, surpassing the majority of the other techniques. Notably, the proposed ESIHE method integrated with the Energy Curve delivered the best results, achieving a PSNR of 29.057, an MSE of 33.982, an SSIM of 0.969, and an FSIM of 0.917678. These results emphasize the significance of leveraging spatial contextual information to significantly improve image quality

Keywords: Color Image Enhancement, Image Exposure, Low Contrast Image, Spatial Contextual Information, Energy Curve.

1.INTRODUCTION

Despite advancements in camera technology, capturing images in low-light conditions remains a challenge, particularly in open areas. These situations often result in images with reduced contrast and diminished clarity. Enhancing such low-light images continues to be an essential focus in image processing research. The limited exposure or coverage in a photograph often affects its brightness or dimness, leading to a lack of clarity in the image. To address this issue and the quality of such images can be improved, various image enhancement algorithms can be applied. These techniques are selected based on the specific characteristics and requirements of the image, enabling better brightness, contrast, and overall appearance. Various histogram-based techniques are commonly used to enhance image quality, with histogram equalization (HE) being a popular choice due to its simplicity. HE improves contrast by spreading pixel intensity values.

Across the full range, resulting in a more balanced intensity distribution. This process enhances details in both dark and bright areas. However, directly the application of HE can alter the mean brightness, prompting the development of advanced methods to address such issues effectively. Image enhancement significantly improves visual quality and

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usability across various fields, including medical imaging (X-rays) and satellite imaging. It also enhances urban planning and environmental monitoring through improved satellite imagery. Image enhancement plays a vital role in security and surveillance by improving video clarity for better activity identification and analysis. It is also crucial for detailed image analysis in scientific research and for enhancing visual appeal in photography and cinematography, thereby increasing the functional and aesthetic value of images across various domains. Dealing with low-resolution or blurry photos, controlling changing lighting conditions, and striking a balance between noise reduction and the preservation of important details are some of the difficulties that image enhancement encounters. Techniques must be versatile to accommodate various image types and scenarios, such as tailoring enhancements for security footage versus medical scans, each requiring specific adjustments.

Despite its difficulties, image enhancement is essential for real-world applications because it makes visual information easier to understand. It facilitates precise medical diagnosis, increases the clarity of security monitoring, improves the visual quality of media and photography, and facilitates in-depth data analysis in scientific studies. Addressing the challenges of image enhancement is crucial. The process is necessary to overcome limitations that often affect images captured by various devices. Image enhancement techniques play a vital role in addressing application-specific challenges, ensuring images are both effective and visually appealing. Among these, histogram equalization is a widely used method, with numerous adaptations tailored to specific needs. This paper examines various image enhancement algorithms built on the principles of histogram equalization.

2.LITERATURE SURVEY

The camera struggles to capture high-quality photos in low-exposure and underwater conditions, Current methods are unable to effectively reduce noise or improve clarity in such challenging environments. Techniques like CLAHE and BBHE have proven inadequate for addressing these issues. Despite advancements in imaging technology, low-exposure problems persist, particularly in underwater or low-light scenarios, where shadow areas in high dynamic range settings often exhibit underexposure artifacts[1]. These issues arise due to imperfect aperture, which directly influences the brightness or darkness of image elements [2].

The first method introduced is Recursive Exposure-based Sub-image Histogram Equalization (R-ESIHE), which builds upon the ESIHE [1,2,16] method. R-ESIHE applies the ESIHE iteratively to an image until the change in exposure values between iterations is smaller than a set threshold. The second method, Recursively Separated Exposure-based Sub-image Histogram Equalization (RS-ESIHE), differs by dividing the histogram into multiple sub-histograms based on distinct exposure thresholds, followed by equalizing each sub-histogram. Both methods incorporate histogram clipping to avoid over-enhancement of the image. Improper aperture and shutter speed settings on a camera can cause low exposure in low-light conditions, affecting the brightness or darkness of each element in an image [2].

Because of its simplicity and convenience of usage, Histogram Equalization (HE) is a widely used contrast enhancement technique [3]. Modifying pixel value ranges it enhances visual contrast and finds extensive use in domains such as object detection and medical imaging. However, because HE maintains the average pixel values before and after the procedure, it has disadvantages, including the potential to produce photos that are either over- or under-saturated.

Bi-Histogram Equalization (BHE) divides the histogram into two sub-regions, or sub-histograms, to solve image brightness problems. One variant that is particularly effective with low-brightness or dimly illuminated images is Brightness Preserving Bi-Histogram Equalization (BBHE). BBHE [5,6]affects the overall brightness of the image by dividing and equalizing the histogram according to average brightness.

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Figure 1: Images considered for experimentation

(A) to (H)

Contrast Limited Adaptive Histogram Equalization (CLAHE) [7-9] improves visual contrast by dividing the image into smaller tiles and applying histogram equalization to each. To prevent excessive noise amplification and reduce the risk of over-enhancement or unwanted artifacts—common issues in standard histogram equalization—it limits the contrast increase within each tile.

Dualistic Sub-Image Histogram Equalization (DSIHE) [10–12] is an image processing technique that separates the histogram of an image into two equal parts at the median intensity level. To enhance contrast, each of these sub-histograms is then equalized independently.

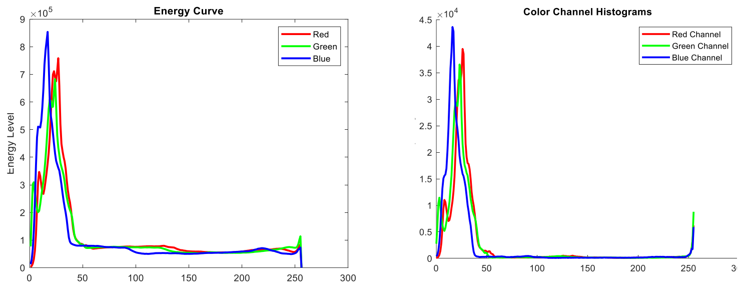

Figure 2: Energy Curve and Histogram of image (H)

This method guarantees uniform pixel distribution throughout sub-histograms, improving localized contrast while maintaining small details. By combining the equalized sub-histograms, DSIHE creates a final image with better contrast and balanced intensity, in contrast to normal histogram equalization, which frequently results in over-enhancement and detail loss. Notwithstanding its benefits, this method has significant drawbacks that reduce its efficacy in difficult situations like dim lighting or submerged surroundings.

Low contrast reduces the perceived quality [13-14] of images and can introduce limitations in captured photographs. Contrast enhancement techniques are used to improve the visibility of visual details, especially in images taken under low light or poor exposure conditions, resulting in clearer and more appealing visuals.

This method improves contrast by applying adaptive histogram equalization to individual image tiles instead of the entire image. The tiles are aligned using a scattered range of values, and a bilinear interpolation ensures smooth transitions, resulting in an image with enhanced overall contrast. Singh and Kapoor introduced the exposure-based sub-image histogram equalization (ESIHE) [15–17] technique, which separates images according to their image exposure threshold to enhance low-exposure photos. Low-exposure photos have a limited dynamic range, which results in low contrast. Histogram bins are concentrated in the darker gray levels of low-intensity images and in the brighter regions of high-intensity images, respectively, resulting in low contrast. Enhancing contrast in low-exposure photos is still a little-studied topic, despite the fact that there are numerous techniques for general contrast improvement. In order to tackle this particular difficulty, this work presents two extensions of ESIHE [2,15].

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3. PROPOSED METHOD FOR HIGH PSNR

The proposed approach addresses the limitations of the previous method and manages different conditions more effectively. Instead of relying on a histogram, it employs an Energy Curve [3], allowing for improved performance by applying histogram equalization directly to the energy distribution.

3.1 Finding Energy Curve (E)

The energy curve calculates the energy for each pixel value, unlike a traditional histogram. Let I represent an image with pixel values x(i,j), where i and j are the spatial coordinates ranging from 1 to N and 1 to M, respectively. The image has dimensions M x N, and I is defined as a matrix of order d.

for an image (i, j) as $N_{ij}^{d} = \{(i + u, j + v), (u, v) \in N^{d}\}$. The subsystems are used to compute the energy curve of an image,i.e.,$(u, v) \in \{(\pm 1,0), (0, \pm 1), (1, \pm 1), (-1, \pm 1)\}$.First, calculate each pixel's energy for the entire greyscale range and generate a binary metrics. $B_x = \{b_{ij}, 1 \leq i \leq M, 1 \leq j \leq N\}$,the $b_{ij} = 1$if $X_{ij} > x$;else $b_{ij} = -1$.let $C = \{c_{ij}, 1 \leq i \leq M, 1 \leq j \leq N\}$ other matric is $c_{ij} = 1, \forall (i, j)$.At each pixel X, the energy value E(K) o I is shown below [2] The $[t_1, t_2]$represents the pixel range

$$E(K) = -\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{pq\in N^2{}_{ij}} b_{ij}b_{pq} + \sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{pq\in N^2{}_{ij}} c_{ij}c_{pq} \qquad (1)$$

of an image I, for $x = t_1$, B_x= 1. As the X value increases for a few elements matrix B_x be -1, if $x = t_2$, then the $B_x$be -1. The energy curve is computed throughout the grayscale range of 0 to 255, or E(K), once the original image has been modified based on the range. This curve performs better than a histogram and has qualities that are comparable to those of a histogram because it considers the spatial contextual information of picture pixels with their nearby pixel.

4.PROPOSED METHOD

4.1Proposed ESIHE_Energy Method

This technique uses an energy curve-derived recursive histogram to process photos. By averaging, the recursive methods assess the image histogram. Raw images usually have weak energy curve representations and are not easily seen. To solve this, the energy curve is refined using the R-ESIHE approach, which improves its informational content for better visual display and improved exposure management.

4.2 Calculation of Exposure of Image

$$\text{exposure} = \frac{\sum_{K=0}^{L-1} E(K)K}{L\sum_{K=0}^{L-1} E(K)} \qquad (2)$$

The total number of grayscale levels is denoted by L, and the energy curve is represented by E(x). The boundary value splits the image into underexposed and overexposed regions based on exposure. If the exposure value is below 0.5, the image is underexposed, and if it exceeds 0.5, the image is overexposed.

$$X_i = L(1 - \text{exposure}) \qquad (3)$$

4.3 Clipping of the Energy curve

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The energy curve of the image is calculated by the E and used to cut the image and establish the threshold. The values of the binomial picture are combined, and the grayscale image is converted into a matrix. Xpdf is used to compare the threshold level and determine the average energy levels.

$$T_c = \frac{1}{L}\sum_{K=0}^{L-1} E(K) \qquad (4)$$

$$E_c(K) = \begin{cases} E(K), E(K) < T_c \\ T_c, \quad E(K) \geq T_c \end{cases} \qquad (5)$$

5.EQUALIZATION PROCESS

The natural image is divided into two regions, WL and WU, based on the exposure threshold value Xi, with WL covering grayscale values from 0 to Xi−1 and WU covering values from Xi to L−1. The probability density functions (PDFs) of these sub-images are defined by PL(K) and PU(K), where the sum of pixels is denoted by NL and NU. The cumulative distribution functions (CDFs) of each image are represented by CL(K) and CU(K), as shown in equations 8 and 9.

$$P_L(K) = {}^{E_c(K)}/_{N_L} \; for\; 0 \leq K \leq X_i - 1 \qquad (6)$$

$$P_U(K) = {}^{E_c(K)}/_{N_U} \; for\; X_i \leq K \leq L - 1 \qquad (7)$$

$$C_L(K) = \sum_{K=0}^{X_i-1} P_L(K) \qquad (8)$$

$$C_U(K) = \sum_{K=X_i}^{L-1} P_U(K) \qquad (9)$$

Using the transfer function as a guide, equalize and combine four sub-images into one.

$$F_L = X_i C_L \qquad (10)$$

$$F_U = (X_i + 1) + (L - X_i + 1)C_U \qquad (11)$$

Where F_L and F_U are transfer functions.

5.1ESIHE_Energy Algorithm

To begin, calculate the energy curve of the image, denoted as E(K). Next, determine the threshold value Xi and assess the exposure level. Clip the energy Ec(K) according to the threshold Tc. Using the threshold Xi, split the energy curve into two distinct sub-sectors. Perform histogram equalization on each of these sub-sectors individually. Finally, combine the processed smaller images to reconstruct the larger image.

6.RESULTS ANALYSIS

The set of images used for the experimental analysis is presented in Figure 1. Eight distinct low-exposure color images, labeled A through H, were processed using eight different image enhancement algorithms. The results obtained from these experiments are summarized and displayed in Tables 1 through 4.

Table 1: PSNR Comparison Across Various Image Enhancement Methods, I: Image, Ave: Average

I	HE	BBHE	CLA HE	DSI HE	R_ ESI HE	RS_ ESI HE	ESHI HE	ESI HE_ Energy
A	4.791	21.543	24.157	6.241	14.874	4.582	14.533	27.166

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B	5.717	21.806	14.945	8.799	16.182	6.479	16.055	28.323
C	6.303	21.336	14.941	11.194	16.264	5.803	16.139	32.686
D	6.483	22.900	18.993	6.691	18.488	6.565	18.212	22.905
E	5.776	17.480	19.914	8.587	13.471	6.190	13.046	20.705
F	9.175	13.403	8.080	10.404	18.967	11.426	18.940	37.437
G	7.480	16.939	10.970	9.731	19.940	9.223	19.633	34.667
H	7.169	19.644	12.947	10.516	12.504	9.521	12.000	28.570
Ave	6.612	19.381	15.618	9.020	16.336	7.474	16.070	29.057

To provide a detailed illustration, the histogram and energy curve of image H are shown in Figure 2. Specifically, the third row in this figure represents the histogram of the enhanced image processed using the ESIHE_Energy method. It is evident from this histogram that pixel intensities are more uniformly distributed across the entire range of 0 to 255, indicating a significant improvement in contrast and detail enhancement.

Table 2: Entropy Comparison Across Various Image Enhancement Methods

I	HE	BBHE	CLA HE	DSI HE	R_ ESI HE	RS_ ESIHE	ESHI HE	ESIHE_ Energy
A	2.975	2.795	0.093	3.245	4.320	3.218	3.901	3.437
B	5.079	5.277	0.432	5.496	5.866	5.746	5.608	5.363
C	3.813	4.279	0.373	4.195	4.342	4.790	4.848	4.356
D	1.843	1.965	0.045	1.942	3.523	1.940	2.567	2.121
E	5.131	5.289	0.454	5.453	5.717	5.771	5.501	5.364
F	5.420	5.803	0.771	6.462	6.259	6.256	6.448	5.975
G	4.985	5.547	0.484	5.987	5.779	6.007	6.167	5.481
H	5.671	5.769	0.491	6.245	6.578	6.544	6.325	6.100
Ave	4.364	4.590	0.393	4.878	5.298	5.034	5.171	4.775

Table 3: SSIM Comparison of Various Image Enhancement Methods

I	HE	BBHE	CLA HE	DSI HE	R_ ESIHE	RS_ ESIHE	ESHI HE	ESIHE_ Energy
A	0.019	0.560	0.642	0.024	0.138	0.020	0.116	0.620
B	0.063	0.798	0.130	0.100	0.427	0.027	0.408	0.918
C	0.076	0.435	0.487	0.404	0.395	0.084	0.375	0.899
D	0.065	0.737	0.010	0.069	0.447	0.094	0.576	0.494
E	0.059	0.338	0.110	0.104	0.202	0.047	0.184	0.536
F	0.241	0.523	0.087	0.262	0.664	0.307	0.642	0.984
G	0.088	0.573	0.120	0.184	0.591	0.061	0.535	0.972
H	0.215	0.826	0.022	0.358	0.413	0.254	0.386	0.924

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Ave	0.103	0.599	0.201	0.188	0.410	0.112	0.403	0.793

Table 4: FSIM Comparison Across Various Image Enhancement Methods

I	HE	BBHE	CLA HE	DSI HE	R_ ESIHE	RS_ ESIHE	ESHI HE	ESIHE_ Energy
A	0.422	0.773	0.751	0.328	0.607	0.412	0.595	0.920
B	0.523	0.931	0.520	0.539	0.833	0.584	0.829	0.985
C	0.543	0.884	0.664	0.615	0.831	0.587	0.824	0.998
D	0.314	0.756	0.850	0.275	0.686	0.468	0.689	0.965
E	0.564	0.862	0.688	0.560	0.760	0.614	0.761	0.898
F	0.581	0.772	0.545	0.600	0.881	0.672	0.877	0.998
G	0.477	0.843	0.705	0.540	0.918	0.554	0.915	0.998
H	0.634	0.919	0.761	0.691	0.819	0.720	0.823	0.990
Ave	0.507	0.842	0.686	0.518	0.792	0.576	0.789	0.969

Further, Figure 3 demonstrates the enhancement results for all eight images using the eight different methods. The top row of this figure displays the original low-exposure input images, while the subsequent rows present the corresponding enhanced images for each method. The final row highlights the output generated by the proposed ESIHE_Energy method. Notably, this method produces images with significantly improved visibility compared to the original inputs.

For instance, in the case of image H, the original input image contains very little visible information due to its low exposure. However, after applying the proposed enhancement method, much more visual detail becomes discernible, which validates the effectiveness of the ESUHE_Energy technique.

For evaluating the performance of various image enhancement techniques, five key comparative metrics are utilized. These metrics include Peak Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE), Entropy, Structural Similarity Index (SSIM) [22], and Feature Similarity Indexing Method (FSIM). Each of these metrics provides a different perspective on image quality, allowing for a comprehensive assessment. PSNR measures the ratio between the maximum possible signal and the noise that affects the image, making it useful for gauging overall image fidelity. MSE quantifies the average squared differences between corresponding pixels, giving an indication of error magnitude. Entropy assesses the information content of the image, reflecting its richness in detail. SSIM evaluates the perceptual similarity between two images, focusing on luminance, contrast, and structure. FSIM, on the other hand, incorporates low-level features like edges and gradients to gauge similarity more accurately.

Eight distinct image enhancement techniques were examined in a sequential manner. These methods include HE, BBHE, CLAHE, DSIHE, ESIHE, Recursive ESIHE (R_ESIHE), Recursive Sub-Image Histogram Equalization (RS_ESIHE), and ESIHE integrated with an energy curve approach (ESIHE_Energy).

To evaluate the effectiveness of these techniques, each method was applied to a set of eight low-exposure color images. The results were compared based on the average values of the aforementioned metrics across all images. This comparative analysis aimed to identify which method produced the best overall enhancement in terms of clarity, detail, and structural similarity.

A higher Peak Signal-to-Noise Ratio (PSNR) signifies more effective noise reduction and greater retention of fine details in an image. Among the evaluated methods, ESIHE_Energy stands out by delivering a PSNR of 29.57, which

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demonstrates its exceptional capability to minimize noise while maintaining crucial image features. This result clearly indicates that ESIHE_Energy is the most proficient technique in preserving image quality after processing. Additionally, BBHE, which achieves a PSNR of 19.38, also performs well, highlighting its ability to reduce noise while keeping significant image details intact. On the other hand, HE exhibits the poorest outcome, with a PSNR value of only 6.612, reflecting insufficient noise suppression and a substantial loss of image detail. In essence, these PSNR values provide a quantifiable measure of each method's efficiency in image enhancement, where a higher PSNR correlates with clearer, less noisy images. The disparity in values emphasizes the superiority of ESIHE_Energy and BBHE over HE in achieving optimal noise reduction without compromising the integrity of image details.

The Mean Squared Error (MSE) serves as a key indicator for evaluating the accuracy of image enhancement techniques by calculating the average of the squared differences between the original image and the enhanced version. A smaller MSE value is desirable, as it signifies a closer resemblance of the enhanced image to the original, with fewer distortions or errors introduced during the enhancement process. Among the evaluated methods, the ESIHE_Energy technique achieves the lowest MSE value of 33.982, implying that it produces minimal error and offers high fidelity in preserving the original image details. Similarly, the BBHE method, with an MSE of 312.775, performs relatively well by keeping error levels low. However, the HE method demonstrates a significant deviation from the original images, evident from its notably high MSE value of 4387.683, which indicates substantial errors and reduced image quality following enhancement.

Entropy is a fundamental metric used to assess the level of randomness or structural complexity in an image. It quantifies how much detailed information is present within the image by examining the distribution of pixel intensities. A higher entropy value signifies that pixel values are more evenly spread across different intensity levels, which usually corresponds to an image containing greater visual detail and richer texture.

In this context, the technique R_ESIHE achieves the highest entropy score of 5.298, which clearly indicates a superior enhancement in image detail. This high value suggests that the method effectively redistributes pixel intensities, resulting in a more complex and visually appealing output. Additionally, other methods, such as ESIHE, with an entropy of generated using various techniques listed in the first column.5.171, and R_ESIHE_Energy, which records an entropy of 4.775, also demonstrate commendable performance in improving image detail by boosting the overall randomness of pixel intensities.

On the other hand, CLAHE produces the lowest entropy value of 0.393, implying that it fails to enhance the details significantly. The low entropy score suggests limited complexity in the enhanced images, resulting in less visual richness and a poorer distribution of pixel intensities when compared to the other methods.

The Structural Similarity Index (SSIM) is a metric commonly used to measure the degree of resemblance between two images, focusing on the preservation of structural details. A higher SSIM score reflects better maintenance of the original image's structure, as well as improved visual quality in the processed image. In this context, the method referred to as ESIHE_Energy demonstrates superior performance by achieving the highest SSIM value of 0.965. This score indicates that ESIHE_Energy effectively retains fine structural details and ensures excellent visual fidelity. Similarly, BBHE also performs well with an SSIM value of 0.842, signifying its capability to maintain structural features to a considerable extent. In contrast, the standard histogram equalization (HE) method yields the lowest SSIM score of 0.507. This result highlights HE's limited ability to preserve structural information, which may lead to noticeable visual distortion or degradation in the enhanced image.

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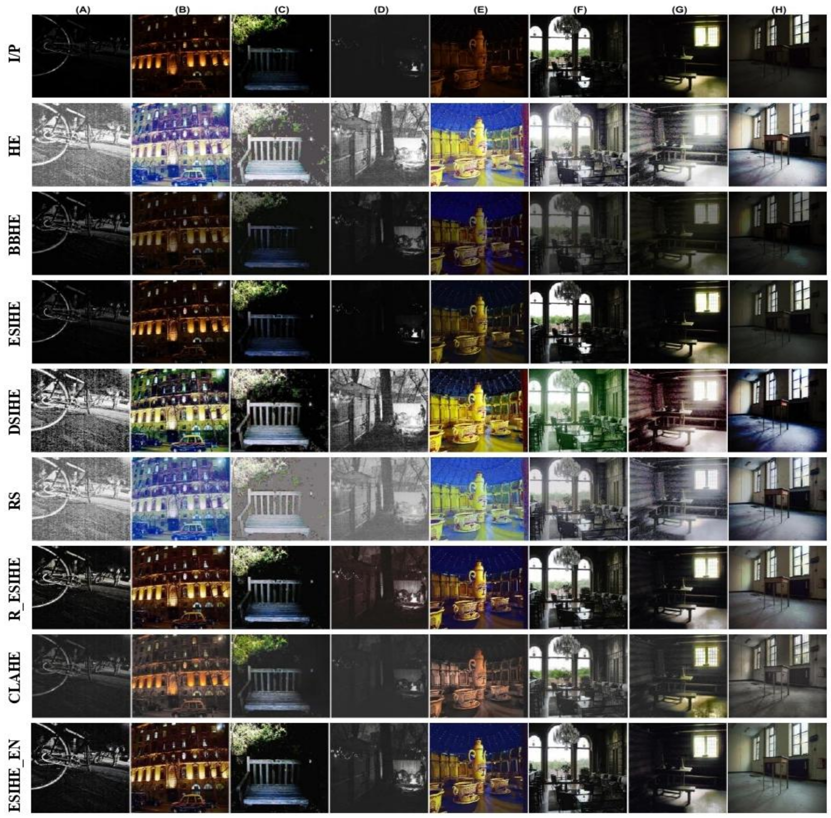

Figure.3: *The first row contains the input images, while the subsequent rows display enhanced images*

The FSIM (Feature Similarity Index Measure) serves as a metric for assessing how similar two images are by focusing on key features that are critical to human visual perception. Essentially, it gauges how well an image retains important structural and perceptual elements when compared to its original version. A higher FSIM score reflects superior preservation of these important features.

Among the techniques compared, ESIHE_Energy achieves the highest FSIM score of 0.793, signifying that it excels in maintaining crucial visual details and features. This high score indicates that the processed image remains visually close to the original in terms of essential perceptual qualities. Another technique, BBHE, also performs reasonably well with an FSIM score of 0.593, demonstrating good preservation of key image features.

On the other hand, HE yields the lowest FSIM score of 0.103, indicating significant degradation of

important image details. This low score implies that the method likely results in a substantial loss of critical visual elements, which may negatively affect the perceived quality of the processed image.

To conclude, ESIHE_Energy consistently stands out as the most effective method across a range of evaluation criteria. Its performance is particularly impressive in minimizing noise (as indicated by high Peak Signal-to-Noise Ratio, or PSNR), reducing errors (low Mean Squared Error, or MSE), maintaining the structural integrity of images (Structural Similarity Index, or SSIM), and preserving key image features (Feature Similarity Index, or FSIM). Additionally, BBHE demonstrates reliable results in multiple performance metrics, making it another dependable option for image enhancement tasks.

In contrast, Histogram Equalization (HE) consistently shows the poorest outcomes in several key aspects. Its weak performance is especially evident in maintaining brightness consistency (measured by Absolute Mean Brightness

Error, or AMBE), reducing noise (PSNR), and retaining both structural and feature-based details (SSIM and FSIM). Consequently, HE emerges as the least effective technique among the ten image enhancement methods evaluated.

7. CONCLUSIONS

The proposed method leverages an energy curve to enhance image quality by implementing an advanced histogram equalization strategy. Traditional image processing techniques face significant challenges in underwater environments and low-light conditions, as they struggle to enhance image clarity or effectively suppress noise for improved visual perception. To address these limitations, the suggested technique demonstrates superior performance by effectively enhancing low-exposure images and solving issues related to inadequate lighting. A comparative evaluation was conducted using ten different image enhancement techniques applied to a dataset of eight low-exposure color images. The performance was assessed using six widely recognized metrics, including AMBE, Peak Signal-to-Noise Ratio (PSNR), Entropy, SSIM, and FSIM. The results consistently showed that the ESIHE_Energy method surpassed other enhancement techniques in terms of noise reduction, minimizing image distortion, and preserving key structural details and features. Furthermore, techniques such as BBHE (Bi-Histogram Equalization) and RS_ESIHE_Energy also displayed commendable performance across various metrics, highlighting their potential reliability in image enhancement tasks. In contrast, the standard Histogram Equalization (HE) method was found to be the least effective, exhibiting notable drawbacks in brightness preservation, noise suppression, and retention of structural integrity. This study underscores the advantages of energy curve-based enhancement approaches, particularly ESIHE_Energy, which excels at improving image quality under challenging low-light conditions while maintaining high visual fidelity and structural coherence.

REFERENCES

[1]. K. Singh, R. Kapoor, S.Kr. Sinha, Enhancement of low Exposure Images via Recursive Histogram Equalization Algorithms, Optik - International Journal for Light and Electron Optics (2015),https://dx.doi.org/10.1016/j.ijleo.2015.06.060.

[2]. Kuldeep Singh, Rajiv Kapoor, Image enhancement using Exposure based Sub Image Histogram Equalization, Pattern Recognition Letters, Volume 36, 15 January 2014, Pages 10-14, ISSN 0167-8655, http://dx.doi.org/10.1016/j.patrec.2013.08.024.

[3]. Srikanth, R. & Bikshalu, K.. (2020). Multilevel thresholding image segmentation based on energy curve with the Harmony Search Algorithm. Ain Shams Engineering Journal. 12. 10.1016/j.asej.2020.09.003.https://www.sciencedirect.com/science/article/pii/S2090447920301970.

[4]. Priya, Lakshmi & K. Jayanthi, Pragatheeswaran & Pottakkat, Biju & Govindarajalou, Ramkumar. (2018). Enhancement approach for liver lesion diagnosis using unenhanced CT images.

[5]. T. L. Tan, K.S. Sim and C.P. Tso, Image enhancement using background brightness preserving histogram equalization, Electronic Letters 48 (2012) 155 - 157.

[6]. Y.-T. Kim, "Contrast enhancement using brightness preserving bihistogram equalization," IEEE Trans. Consum. Electron., vol. 43, no. 1, pp. 1–8, Feb. 1997.

[7]. Z. Yao, Z. Lai, C. Wang and W. Xia, "Brightness preserving and contrast limited bi-histogram equalization for image enhancement," 2016 3rd International Conference on Systems and Informatics (ICSAI), 2016, pp. 866-870, doi: 10.1109/ICSAI.2016.7811072.

[8]. Srikanth, R., Sowmya, K.L., Anjana, S., Vamshi, G., Reddy, A.R.M. (2022). Improved Image Enhancement of Natural Images with Median Mean-Based Sub-Image Clipped Histogram Equalization. In: Ranganathan, G., Fernando, X., Shi, F., El Allioui, Y. (eds) Soft Computing for Security Applications . Advances in Intelligent Systems and Computing, vol 1397. Springer, Singapore. https://doi.org/10.1007/978-981-16-5301-8_61.

[9]. C.H. Lee, L.H. Chen, W.K. Wang, Image contrast enhancement using classi-fied virtual exposure image fusion, IEEE Trans. Consumer Electron. 58 (2012) 1253–1261.

[10]. Y. Wang, Q. Chen, and B. Zhang, "Image enhancement based on equal area dualistic sub-image histogram equalization method," IEEE Trans. Consum. Electron., vol. 45, no. 1, pp. 68–75, Feb. 1999

Journal of Information Systems Engineering and Management
2025, 10(49s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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[11]. Zarie, Majid & Hajghassem, Hassan & Eslami Majd, Abdollah. (2018). Contrast Enhancement Using Triple Dynamic Clipped Histogram Equalization Based on Mean or Median. Optik. 175. 10.1016/j.ijleo.2018.08.082.
[12]. H. Singh, A. Kumar, L. K. Balyan, and H. N. Lee, "Optimally sectioned and successively reconstructed histogram sub-equalization based gamma correction for satellite image enhancement," Multimedia Tools Appl., vol. 78, pp. 20431–20463, Mar. 2019.
[13]. Sonali, S. Sahu, A. K. Singh, S. P. Ghrera, and M. Elhoseny, "An approach for de-noising and contrast enhancement of retinal fundus image using CLAHE," Opt. Laser Technol., vol. 110, pp. 87–98, Feb. 2019.
[14]. Reza, A.M. Realization of the Contrast Limited Adaptive Histogram Equalization (CLAHE) for Real-Time Image Enhancement. The Journal of VLSI Signal Processing-Systems for Signal, Image, and Video Technology 38, 35–44 (2004).
[15]. W. Wang, X. Wu, X. Yuan and Z. Gao, "An Experiment-Based Review of Low-Light Image Enhancement Methods," in IEEE Access, vol. 8, pp. 87884-87917, 2020, doi: 10.1109/ ACCESS. 2020.2992749.
[16]. K. S. Sim, C. P. Tso and Y. Y. Tan, Recursive Sub-Image Histogram Equalization Applied to Gray Scale Images, Pattern Recognition Letters 28 (2007) 1209-1221.
[17]. K. Srinivas, A. K. Bhandari and A. Singh, "Exposure-Based Energy Curve Equalization for Enhancement of Contrast Distorted Images," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 12, pp. 4663-4675, Dec. 2020, doi: 10.1109/TCSVT.2019.2960861.
[18]. S. D. Chen, A New Image Quality Measure for Assessment of Histogram Equalization-Based Contrast Enhancement, Digital Signal Processing 22 (2012) 640–647.
[19]. Soong-Der Chen, 2014. A Statistical Evaluation of Image Quality Analyzer for Assessment of Histogram Equalization-based Contrast Enhancement Methods. Journal of Applied Sciences, 14: 18-25. DOI: 10.3923/jas.2014.18.25
[20]. Singh, Navdeep & Kaur, Lakhwinder & Singh, Kuldeep. (2019). Histogram equalization techniques for enhancement of low radiance retinal images for early detection of diabetic retinopathy. Engineering Science and Technology, an International Journal. 22. 10.1016/j.jestch.2019.01.014.
[21]. Rangu, S.; Veramalla, R.; Salkuti, S.R.; Kalagadda, B. Efficient Approach to Color Image Segmentation Based on Multilevel Thresholding Using EMO Algorithm by Considering Spatial Contextual Information. J. Imaging 2023, 9, 74. https://doi.org/10.3390/jimaging9040074.
[22]. Asisa Kumar Panigrahy, Shima Ramesh Maniyath, Mithileysh Sathiyanarayanan, Mohan Dholvan, T. Ramaswamy, Sudheer Hanumanthakari, N. Arun Vignesh, S. Kanithan, Raghunandan Swain, "A Faster and Robust Artificial Neural Network Based Image Encryption Technique With Improved SSIM," in IEEE Access, vol. 12, pp. 10818-10833, 2024, doi: 10.1109/ACCESS.2024.3353294.

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