

Adaptive Gamma Weighted Tri Histogram Equalisation

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ABSTRACT

This paper introduces a novel image enhancement technique called Adaptive Gamma Weighted Tri Histogram Equalisation (AGWTHE), designed to improve the visual quality of both grayscale and color images. The proposed method incorporates adaptive gamma correction into a tri histogram equalisation framework, enhancing image contrast while preserving brightness and details. Initially, the image histogram is adaptively clipped using a gamma weighted function to prevent over enhancement and detail loss. The resulting histogram is then partitioned into three sub histograms based on statistical features such as mean and standard deviation. Each sub histogram undergoes individual histogram equalisation, followed by a fusion process to generate the final enhanced image. Experimental evaluations demonstrate that AGWTHE effectively enhances image quality while maintaining natural appearance. The method outperforms several state of the art techniques in both subjective and objective assessments, as validated by metrics including Entropy, FSIM, VSI, and GMSD. The proposed approach is robust, adaptive, and suitable for a wide range of image types and applications.

Keywords: Lithium-ion battery, State of Health, Deep learning, Resampling

1. INTRODUCTION

Image enhancement is a fundamental step in many image processing applications, especially in scenarios where the captured images suffer from poor lighting, low contrast, or uneven brightness. Image enhancement plays a crucial role in the broader process of image analysis, as it aims to improve image quality and highlight important details, particularly in low luminance areas. Enhancement techniques can be broadly categorized into two domains: frequency domain and spatial domain methods [1]. Frequency domain techniques operate on the transformed frequency components of the image, while spatial domain techniques such as contrast en-

hancement act directly on the pixel intensity values.

Among the various spatial domain approaches, Histogram Equalisation (HE) remains one of the most commonly employed techniques. HE works by redistributing pixel intensities to span the entire available range, thereby increasing the dynamic range and enhancing image contrast. However, traditional HE has notable drawbacks: it often alters the mean brightness of the image, leading to undesirable effects such as over-enhancement or under-enhancement. To address these limitations, many advanced variants of HE have been developed over the years.

The literature on histogram equalisation is extensive and evolving. In 1997, Kim introduced Brightness Preserving Bi-Histogram Equalisation (BBHE) [2], which partitions the histogram into two sections at the mean intensity and applies equalisation to each part independently. Following this, Dualistic Sub-Image Histogram Equalisation (DSIHE) was proposed by Wang [3], which improves brightness preservation by dividing the histogram at the median intensity.

Recursive Mean Separate Histogram Equalisation (RMSHE) [4], introduced by Chen, recursively applies BBHE using the average intensity for segmentation. A related technique, Recursive Sub-Image Histogram Equalisation (RSIHE) [5], performs recursive splitting based on the median intensity. These methods were further refined in RSWHEM (Recursive Separated and Weighted Histogram Equalisation using Mean), which introduces a weighted accumulation factor α to enhance both contrast and mean brightness retention. RSWHE [6] further enhances brightness preservation by applying a weighting function based on a power-law distribution during the recursive segmentation.

The Statistic-Separate Tri-Histogram Equalisation (SSTHE) method, proposed by Lin et al. [8], divides the histogram into three segments based on the mean and standard deviation of the image. Each sub-histogram is processed independently. However, SSTHE may introduce visual artefacts, especially when the middle segment contains relatively few pixels.

Exposure-based Sub-Image Histogram Equalisation (ESIHE), developed by Kuldeep Singh [10], specifically targets low-exposure grayscale images. It employs a histogram clipping strategy based on a threshold value to enhance contrast while preserving entropy.

In 2018, Unsharp Masking Histogram Equalisation (UMHE), suggested by Shubhi Kansal [11], utilized an unsharp filter before histogram clipping and equalisation. This method effectively reduces over-enhancement but

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fails to maintain the image's mean brightness.

Also in 2018, Plateau Limit-Based Tri-Histogram Equalisation, introduced by Abhisek Paul [12], first clips the histogram based on a threshold and then segments it into three regions. Histogram equalisation is then applied independently to each part. This approach effectively avoids over-enhancement and better preserves brightness.

Gamma correction, a nonlinear operation used to encode and decode luminance values, offers a simple yet effective approach to control image brightness. Nonetheless, selecting an appropriate gamma value remains challenging, as a fixed gamma value may not be suitable across varying illumination conditions or different regions within an image. To address this limitation, Adaptive Gamma Equalization (AGE) has emerged as a promising technique that dynamically adjusts the gamma value based on local image characteristics. AGE methods [13-18] intelligently tailor the enhancement process by analyzing image histograms or local statistics, ensuring that dark regions are brightened without saturating bright areas. This adaptive behavior leads to improved contrast, better preservation of edges, and enhanced visual perception. AGE is particularly useful in fields such as medical imaging, remote sensing, and surveillance, where maintaining detail and clarity is crucial.

In 2023 Jing Wu, Shuang Wu and Bo Sun proposed a method for enhancing rock mass fracture images using generalized gamma correction (GGC) [19]. The approach adapts to the unique characteristics of geological images, improving the visibility of fractures by adjusting the gray histogram dynamically.

In 2024 Ali Hakem Alsaedi, Suha Mohammed Hadi and Yarub Alazzawi proposed The AGCC model which enhances low-light images by combining adaptive gamma correction with color correction techniques (AGCC)[20]. The approach aims to restore color balance and improve image clarity, demonstrating effectiveness across various datasets.

Building upon these advancements, the proposed method introduces an adaptive gamma Weighted Tri-Histogram Equalisation framework. Instead of using absolute clipping, it applies a weighted clipping mechanism using a power-law transformation, which helps mitigate both over- and under-enhancement. The histogram is then divided into three regions based on the images mean and standard deviation. Each sub-histogram is equalised separately, and the results are combined to generate the final enhanced image. This method balances contrast enhancement with brightness preservation and aims to produce visually natural and detailed outputs.

Table 1 provides the comparison between various HE methods giving its advantages and limitations. The classification of prior works in the table clearly highlights the limitations of prior approaches. These limitations motivate the adoption of a tri-histogram framework, which offers a balanced trade-off between adaptability,

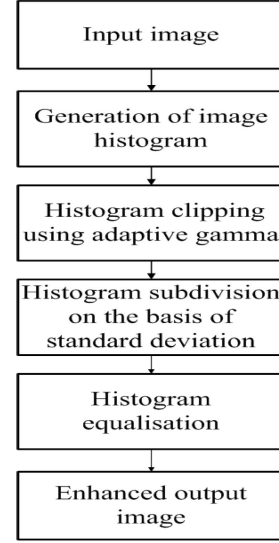


Fig. 1: Flowchart

computational complexity, and enhancement quality.

2. ADAPTIVE GAMMA WEIGHTED TRI-HISTOGRAM EQUALIZATION

To leverage the strengths of both approaches i.e. gamma correction and HE, an Adaptive Gamma Tri-Histogram Equalization (AGTHE) method is proposed here, which integrates adaptive gamma correction with tri-histogram equalization. The proposed method first segments the histogram into three parts to localize enhancement and then applies gamma correction adaptively within each segment. This dual strategy ensures improved contrast enhancement, better brightness preservation, and minimal information loss, resulting in visually pleasing and detail-rich images. The suggested enhancement technique, called Weighted Tri-Histogram Equalization, operates on a modified histogram that has been weighted and partitioned into three segments. These segments are defined based on the standard deviation of the original histogram. A visual representation of the proposed method is provided in Figure 1.

2.1 Histogram Scaling and Clipping

Histogram scaling refers to stretching or compressing the intensity values of an image to occupy a desired dynamic range. Histogram clipping involves limiting or cutting off the histogram values (typically the number of pixels at certain intensities) beyond a specified threshold to suppress the influence of outlier intensities. Histogram of the image is defined as the number of pixels n_k at corresponding intensity level r_k . Mathematically it is given as:

$$h(r_k) = n_k \quad (1)$$

To achieve a balanced and natural-looking enhancement, a clipping operation is applied to regulate the

Table 1: Comparison of various HE based methods.

Technique	Advantages	Limitations
HE	Simple implementation, improves global contrast	Brightness issues and may produce overenhancement, noise amplification
BBHE	Preserves mean brightness better than HE	Still may not preserve natural appearance perfectly
DSIHE	Improves entropy and preserves brightness then BBHE	May introduce noise and artifacts in enhanced images
RMSHE	Better brightness preservation and natural appearance compared with HE and BBHE	Large recursion may reduce enhancement effect
RSWHE	Improves brightness preservation and avoids over-enhancement	Increased computational complexity and parameter tuning required
SSTHE	Better control of contrast enhancement and brightness preservation	May still produce artifacts in some images
ESIHE	Improves exposure balance and enhances low-contrast images	Enhancement may be uneven if exposure estimation is inaccurate
UMHE	Better brightness preservation and avoids excessive contrast stretching	High computational cost
GCC	Enhances low-light images and controls contrast effectively	high computation complexity
AGCC	Effective for low-contrast and low-illumination images	Slightly higher computational complexity
Proposed	Very Low computational complexity as compared to GCC and AGCC and provide rich details of the image	Should be tested for various fields

image contrast. This involves capping the histogram bins at an upper threshold, which is determined by calculating the average of the histogram's mean and median values.

$$H_n = \text{median}[H(k)] \quad (2)$$

$$H_m = \text{mean}[H(k)] \quad (3)$$

$$H_u = \frac{H_n + H_m}{2} \quad (4)$$

$$H_l = \text{minimum}[h(k)] \quad (5)$$

In the proposed level-mapping scheme, $H_w(k)$ is obtained by using a transformation function $\beta(\cdot)$ to $H(k)$ in the following way:

$$H_w(k) = \beta(H(k)) = \begin{cases} H_u, & \text{if } H(k) > H_u; \\ \left\{ \frac{H(k) - H_l}{H_u - H_l} \right\}^r, & \text{if } H_l \leq H(k) \leq H_u; \\ 0, & \text{if } H(k) < H_l \end{cases}$$

The used transformation function $\beta(k)$ clips the original histogram at an upper threshold limit H_u and at lower threshold limit H_l , the values between upper and lower thresholds are transformed using normalized power law function with index $r > 0$.

The parameter r in the power-law transformation is tuned to manage how much each intensity level is amplified. When $r < 1$ the transformation emphasizes less frequent (lower probability) intensity levels more than the dominant ones. This fractional value of r helps prevent excessive enhancement. Additionally, to further suppress the influence of highly probable intensity levels, the histogram is clipped at a defined upper threshold.

The lower threshold is set to be the minimum value of the histogram which helps to eliminate the intensity levels which have very low probability so that the full dynamic range is utilized.

In several histogram equalization approaches, absolute clipping is applied to limit excessive peaks in the histogram before equalization. Although this prevents extreme peaks from dominating the equalization process, absolute clipping has two major limitations

- It removes excess histogram information abruptly, leading to loss of intensity distribution details.
- The clipped values are discarded rather than redistributed, which may reduce contrast and degrade image details.

To overcome these limitations, the proposed method introduces a weighted clipping mechanism that moderates the clipping process rather than performing a

hard truncation. Hence the weighted clipping process preserves distribution characteristics and also maintains better contrast balance.

The proposed transformation function uses the average of the mean and median of the histogram as the upper threshold limit of the histogram as against the [12] in which upper limit is decided by adjusting the normalized parameter and the maximum value of original PDF. Also the normalized parameter in [12] is adjusted manually, so the proposed method effectively eliminates the need of manual changes as the mean and the median of the image is calculated through programming.

2.1.1 Calculation of limit parameters of sub histogram

The histogram of the image is divided into three sub-histograms, which requires the calculation of the two limit parameters. X_u is the upper limit parameter and X_l is the lower limit parameter respectively. These parameters are calculated using mean and standard deviation of the image, so as to get the enhanced image with less number of artefacts.

$$X_m = \frac{\sum_{i=0}^{L-1} i * H(i)}{\sum_{i=0}^{L-1} H(i)} \quad (6)$$

$$X_s = \sqrt{\frac{\sum_{i=0}^{L-1} \{i - X_m\}^2 * H(i)}{\sum_{i=0}^{L-1} H(i)}} \quad (7)$$

$$X_l = X_0 + X_s \quad (8)$$

$$X_u = X_{L-1} - X_s \quad (9)$$

where X_0 and X_{L-1} are the highest and the lowest intensity of the given image.

2.1.2 Sub-histogram division and equalization

Using the above calculated limit parameters the histogram is subdivided into three sub-histograms. Overall mean brightness of the image is conserved as the middle part of the histogram contains maximum number of the pixels.

The lower part of the histogram ranges from 0 to X_l having the probability density function P_l , middle one ranges from X_l+1 to X_u having probability density function P_m and the upper part ranges from X_u+1 to $L-1$ having the probability density function P_u . Mathematically, the probability density function of the sub-images

is given by:

$$P_l(j) = \frac{H_w(j)}{n_l} \quad \text{for } 0 \leq j \leq X_l; \quad (10)$$

$$P_m(j) = \frac{H_w(j)}{n_u} \quad \text{for } X_l + 1 \leq j \leq X_u; \quad (11)$$

$$P_u(j) = \frac{H_w(j)}{n_m} \quad \text{for } X_u + 1 \leq j \leq L - 1; \quad (12)$$

Each Pdf section is now normalized by dividing the original probabilities by their respective segment weights. After this the CDF will be calculated cumulative density function of sub-images is given as follows:

$$C_l(j) = \sum_{j=0}^{X_l} P_l(j) \quad (13)$$

$$C_m(j) = \sum_{j=X_l+1}^{X_u} P_m(j) \quad (14)$$

$$C_u(j) = \sum_{j=X_u+1}^{L-1} P_u(j) \quad (15)$$

Histogram equalization is performed independently on these sub-histograms. The individual transformation function of each sub-histogram is given as below:

$$T_l = X_l * C_l \quad (16)$$

$$T_m = (X_l + 1) + (X_u - X_l + 1) * C_m \quad (17)$$

$$T_u = (X_u + 1) + (L - X_u + 1) * C_u \quad (18)$$

Using the above functions, independent sub-images are obtained. The final enhanced image is formed by the concatenation of these three images.

3. EXPERIMENTAL RESULTS AND DISCUSSION

We performed various qualitative and quantitative experiments over variety of images using our proposed method. These results are compared with the recently proposed HE-based methods including RSWHE, GGC and AGCC. All these methods are executed in MATLAB with the help of default parameters as stated in each of these methods.

3.1 Quantitative Assessment

Quantitative assessment refers to the objective measurement of image quality after applying enhancement techniques by using numerical metrics. These metrics allows to evaluate and compare the performance of different methods without relying solely on visual judgment. The parameters used here to quantitatively state the visual quality of the image are entropy, Feature Similarity Index Matrix (FSIM), Visual Saliency Induced Matrix (VSI) and Gradient Magnitude Similarity Matrix (GMSD).

Table 2: Entropy of different methods.

Image	Original	RSWHE	ESIHE	GGC	AGCC	Proposed
Flying Bird	5.7580	5.7274	5.7325	5.7491	5.7323	5.7580
Tiger	6.2082	6.1982	6.2013	6.2006	6.1868	6.2077
Sphinx	6.6987	6.6455	6.6796	6.6798	6.6528	6.6888
Gate	7.1454	7.1206	7.1356	7.1445	7.1100	7.1450
Bird	7.0605	7.0109	7.0256	7.0410	7.0124	7.0552
Plane	6.6400	6.6023	6.5935	6.5941	6.5894	6.6220
Average	6.5851	6.5508	6.5613	6.5681	6.5472	6.5794

Table 3: FSIM of different methods.

Image	RSWHE	ESIHE	GGC	AGCC	Proposed
Flying Bird	0.8870	0.9414	0.9189	0.9385	0.9647
Tiger	0.8802	0.9091	0.8785	0.8509	0.9499
Sphinx	0.9278	0.9517	0.8576	0.9203	0.9670
Gate	0.9177	0.9208	0.8976	0.9484	0.9731
Bird	0.8715	0.9643	0.9374	0.9502	0.9758
Plane	0.8802	0.9542	0.9661	0.8972	0.9496
Average	0.8940	0.9372	0.9183	0.9175	0.9633

Table 4: VSI of different methods.

Image	RSWHE	ESIHE	GGC	AGCC	Proposed
Flying Bird	0.9866	0.9839	0.9812	0.9863	0.9922
Tiger	0.9617	0.9775	0.9639	0.9534	0.9876
Sphinx	0.9846	0.9773	0.9714	0.9789	0.9940
Gate	0.9793	0.9776	0.9806	0.9855	0.9938
Bird	0.9731	0.9893	0.9698	0.9823	0.9920
Plane	0.9636	0.9877	0.9888	0.9729	0.9879
Average	0.9748	0.9822	0.9759	0.9765	0.9912

3.1.1 Entropy

Entropy is a statistical measure of randomness or uncertainty. In image processing, it is often used to quantify the amount of information or the complexity of image content. A higher entropy value indicates a richer, more complex image with more detail and variation. It is simple and computationally efficient parameter. It Reflects global image contrast and detail level and useful for quantitative comparison in enhancement tasks. Mathematically, the entropy of the image is calculated as below:

$$Entropy = \sum_{i=0}^{L-1} P(i) \log_2(P(i)) \quad (19)$$

The proposed method is compared with RSWHE, GGC and AGCC methods. Table 2 shows the entropy of the original image and the enhanced images using different methods. The best values are marked in bold. The second best method is shown as italic. For every image, it can be observed that the proposed method gives the best results for entropy. Therefore it can be concluded that the proposed method gives the finer details about the image.

3.1.2 Feature Similarity Index Matrix(FSIM)

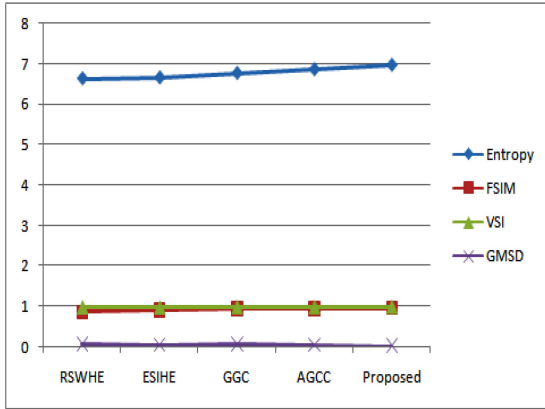
FSIM (Feature Similarity Index) is a full-reference image quality assessment (IQA) metric designed to evaluate the visual similarity between a reference (original) image and a distorted or enhanced version of it. FSIM was introduced by Zhang et al. in 2011 [21][22][23] and is

Table 5: GMSD of different methods.

Image	RSWHE	ESIHE	GGC	AGCC	Proposed
Flying Bird	0.0975	0.0419	0.0619	<i>0.0402</i>	0.0273
Tiger	0.0864	<i>0.0475</i>	0.0722	0.0589	0.0271
Sphinx	0.0600	0.0656	0.0941	<i>0.0461</i>	0.0191
Gate	0.0513	0.0426	0.0486	<i>0.0362</i>	0.0142
Bird	0.1126	<i>0.0277</i>	0.1006	0.0331	0.0207
Plane	0.0787	<i>0.0303</i>	0.0443	0.0562	0.0290
Average	0.0810	0.0543	0.0702	<i>0.0451</i>	0.0229

Table 6: Average computation time (in sec).

Image Size	RSWHE	ESIHE	GGC	AGCC	Proposed
256x256x3	1.45	0.22	1.09	0.90	0.18
321x481x3	2.98	0.23	2.42	2.03	0.19
365x490x3	3.21	0.25	3.11	2.42	0.23
512x768x3	9.87	0.34	7.66	5.44	0.32
600x893x3	10.98	0.39	9.52	6.59	0.37

**Fig. 2: Average result of 100 images**

considered one of the most reliable metrics for correlating with human visual perception. For the better enhanced image this parameter should be close to 1.

$$FSIM = \frac{\sum_{i \in \Omega} S(i) PC_n(i)}{\sum_{i \in \Omega} PC_n(i)} \quad (20)$$

Here, Ω indicates spatial domain. PC_n denotes the phase congruency of the original and enhanced image and $S(i)$ denotes the local similarity of the original and enhanced image at particular pixel i . Table 3 shows the FSIM value for different methods.

The best results are shown in bold and the second best results are shown in italic. It can be observed from the results that except for the image 'plane', the value of FSIM is more closer to 1 for the proposed method. Therefore, the enhanced image has more similarity with the original image for the proposed method.

3.1.3 Visual Saliency-induced Index Matrix (VSI)

VSI is an advanced full-reference image quality assessment [24][25][26] (IQA) metric that evaluates the perceived similarity between a reference image and its processed (e.g., enhanced or compressed) version by integrating visual saliency with other features. It was

introduced by Zhang et al. in 2014, aiming to better align with human visual perception, particularly where humans pay attention in an image.

Let f_1 be the original image and f_2 is the enhanced image. Visual saliency for f_1 and f_2 is denoted by VS_1 and VS_2 . $S(i)$ indicates local similarity of $f_1(i)$ and $f_2(i)$ at pixel location i . $VS_m(i)$ is calculated as maximum of $VS_1(i)$ and $VS_2(i)$. VSI metric between image f_1 and f_2 is defined as:

$$VSI = \frac{\sum_{i \in \Omega} S(i) VS_m(i)}{\sum_{i \in \Omega} VS_m(i)} \quad (21)$$

Here, Ω indicates spatial domain. Table 4 shows the VSI value for different methods.

The best result is shown in bold and the second best result is shown in italic. It can be observed from the results that except for the image 'plane', the value of VSI is more closer to 1 for the proposed method. Therefore, the enhanced image has more similarity with the original image for the proposed method.

3.1.4 Gradient Magnitude similarity deviation (GMSD)

GMSD is a full-reference image quality assessment (IQA) metric that evaluates the perceptual quality degradation of an image by focusing on the gradient magnitude similarity between the reference and the distorted/enhanced image. It was proposed by Wufeng Xue et al. in 2014, designed to be both accurate (closely aligned with human visual perception) and computationally efficient, making it suitable for large-scale image quality evaluation. GMSD [27][28][29][30] indicates the distortion of the image from the original image. Therefore, it should be as low as possible.

The best results are shown in bold. The second best results are shown in italic. It can be concluded from the above observations that the proposed method has the lowest value of the GMSD parameter, thus indicating the least deviation of the enhanced image from the original image.

3.1.5 Computation complexity

Table 6 compares the computation time complexity of the different methods. For comparison we have taken the images of different size and all are color images. As it can be observed that RSWHE method requires maximum time to process all the images as compared to other methods. ESIHE method is also very close to proposed method. Rest all methods computation time is high as compared to proposed method. Hence, the proposed method can be very well utilized in real time applications due to its fast speed and good results which are not obtained by other methods.

Fig. 2 shows the average result of 100 images taken from Berkely Image database. The graph shows the best results for the proposed method.



Fig. 3: Flying bird image: (a) Input (b) RSWHE (c) ESIHE (d)GGC (e) AGCC (f) Proposed



Fig. 4: Tiger image: (a) Input (b) RSWHE (c) ESIHE (d)GGC (e) AGCC (f) Proposed



Fig. 5: Sphinx image: (a) Input (b) RSWHE (c) ESIHE (d)GGC (e) AGCC (f) Proposed



Fig. 6: Gate image: (a) Input (b) RSWHE (c) ESIHE (d)GGC (e) AGCC (f) Proposed

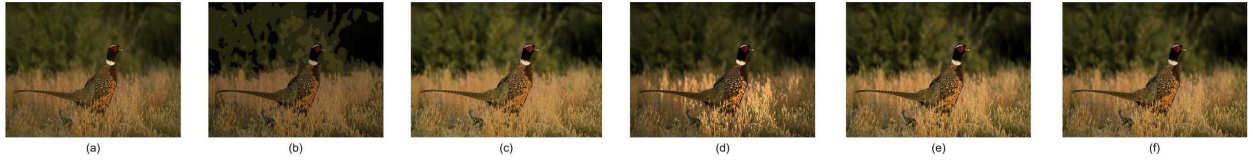


Fig. 7: Bird image: (a) Input (b) RSWHE (c) ESIHE (d)GGC (e) AGCC (f) Proposed



Fig. 8: Plane image: (a) Input (b) RSWHE (c) ESIHE (d)GGC (e) AGCC (f) Proposed

3.2 Visual Quality Assessment

Visual quality shows the quality of the image as perceived by a human. This parameter is subjective in nature. Visual quality assessment helps to judge the annoying artefacts, over-enhancement and unnatural enhancement. Wide varieties of standard images has been taken to test the robustness of the proposed method.

Fig. 3 shows the original image of 'Flying Birds' and its equalised images. RSWHE method produces the image with extra artefacts. ESIHE produces the high

intensities in the middle portion of the image resulting in over-enhancement of the image. Similar results are seen in case of GGC method with lower intensities on the outer edges of the background. AGCC method has shown the better results by reducing the intensities in the middle portion of the image. The proposed method has not only reduced the intensities in the middle portion of the image but also has preserved the natural appearance of the image.

In Fig. 4 the equalised images of 'tiger' is shown.

Table 7: MOS Results.

Methods	Flying Bird	Tiger	Sphinx	Gate	Bird	Plane
RSWHE	1.5	2.2	2.3	1.7	2.4	1.7
ESIHE	4.2	3.4	3.6	3.4	3.8	2.9
GGC	4.3	2.2	2.6	1.9	2.5	4.3
AGCC	4.3	4.2	4.2	3.6	3.8	3.7
Proposed	4.4	4.3	4.1	4.2	4.4	4.5

RSWHE method has resulted in blurred grass in the background. ESIHE method has given better output image with slightly darker grass in the background. GGC method has proved more darker background and the tiger itself has also been made darker. Thus GGC method has resulted in under-enhancement of the image. AGCC method has resulted in improved image with some gloomy area in the output. The proposed method shows better performance in terms of under-enhancement of the image and preserving the natural look of the image.

Fig. 5 shows the equalised images of 'sphinx'. In RSWHE method the edges of background sky has become darker. ESIHE has resulted in over-enhancement of the image. GGC has increased the darker pixels in the background as well as in the middle resulting in the under-enhancement of the image. In AGCC, the middle portion is still brighter. The proposed method has given the better performance in all the aspects with respect to other methods.

Fig. 6 shows the equalised versions of 'gate' image. RSWHE method has introduced dark pixels in the side wall of the image. The road in ESIHE method has become brighter resulting in over-enhancement of the image. The GGC method has increased the brighter pixels in the background sky near tree. The background sky is slightly brighter in AGCC method. The proposed method gives the better results and preserves the natural brightness of the image.

Similarly, it can be observed from Fig. 6 and Fig. 7 that the proposed method outperforms the other methods in terms of contrast enhancement while preserving the natural appearance of the image.

Table 7 shows the mean opinion score (MOS) conducted on the test images to support the visual assessment results. The opinion was taken from the 20 people and the image ratings were given from 1-5, where 1 means worst and 5 corresponds to best. The values from the table shows that proposed method gives better visual quality.

4. CONCLUSION

In this study, a novel Adaptive Gamma Tri-Histogram Equalization (AGTHE) technique for effective image contrast enhancement is proposed. The proposed method combines the strengths of adaptive gamma correction and tri-histogram equalization, allowing dynamic adjustment of image intensity based on local histogram characteristics. By dividing the histogram into three segments and applying region-specific gamma correction,

the method achieves superior balance between contrast enhancement, brightness preservation, and detail retention.

To further improve the robustness of the method, histogram scaling and clipping were applied prior to enhancement to suppress over-enhancement and mitigate the effects of intensity outliers. This preprocessing step plays a critical role in preserving natural brightness and preventing noise amplification.

The performance of the AGTHE method was evaluated through both quantitative metrics (such as entropy, FSIM, VSI, and GMSD) and visual quality assessments. Experimental results demonstrate that AGTHE outperforms conventional techniques like Histogram Equalization (HE), CLAHE, and Bi-Histogram Equalization in terms of visual fidelity and numerical quality scores. Particularly, the method shows strong performance in preserving edge structures (reflected in low GMSD) and perceptual similarity (high VSI and FSIM), making it well-suited for applications such as medical imaging, remote sensing, and low-light photography.

In conclusion, the AGTHE method offers a balanced, adaptive, and perceptually aware solution for image enhancement.

5. FUTURE SCOPE

While the proposed Adaptive Gamma Tri-Histogram Equalization (AGTHE) method demonstrates significant improvements in contrast enhancement and perceptual quality, several promising directions remain open for future exploration to further enhance its applicability and performance like for applications in real-time systems, such as video surveillance, autonomous vehicles, or embedded medical devices, optimizing the AGTHE algorithm for low-latency, real-time performance is essential. Implementation using Field Programmable Gate Arrays (FPGAs), GPUs, or dedicated image processors could significantly accelerate processing speed while maintaining enhancement quality.

Currently, the gamma values and clipping thresholds are adaptively determined based on histogram features. These parameters could be learned dynamically using machine learning techniques, making the method more intelligent and scene-aware. For example, reinforcement learning or optimization algorithms could be employed to adjust enhancement strength based on image content. AGTHE can be customized for specialized domains such as Medical imaging, Underwater imaging and Remote sensing or satellite imagery, where contrast enhancement can help highlight terrain features or man-made structures.

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