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An Automated Contrast Enhancement Technique for Remote Sensed Images

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Abstract

Remote sensing images often exhibit lower contrast than usual. Contrast Limited Adaptive Histogram Equalization (CLAHE) is a well-established and robust local contrast enhancement algorithm, renowned for its high-quality results, particularly in the medical domain. In this article, we introduce an automated contrast-limit adaptive histogram equalization method applied on remote sensing images, drawing inspiration from CLAHE. Our proposed algorithm incorporates automatic outlier detection blocks into the standard CLAHE framework, addressing the limitation of relying on a predetermined single clip-limit as is preset in traditional CLAHE. Instead, our approach adapts multiple clip-limits, one for each Contextual Region (CR), rather than a global clip-limit used in the original algorithm. First, the algorithm divides the image into tiles based on proximity, called contextual region, then it computes the histogram for each CR. In this stage, the CLAHE depends on clip-limit as pre-set user input to clip the intensities above clip-limit, then it redistributes the deducted intensities over the quantization range. On the contrary, the proposed algorithm calculates outliers of each CR and considers a clip-limit for the CR. Next, histogram equalization is performed on the modified CR histogram. Finally, Image is reconstructed by applying bilinear interpolation to outcome CRs. Experimental and comparison results showed that the proposed technique provides better results than classic CLAHE for remote sensing images on DOTA dataset. Moreover, the proposed algorithm achieves an improvement of 27.960 for PSNR and 3.271 for CG.

Keywords: *Image Processing, Remote sensing, Contrast Enhancement, CLAHE and satellite Images*

I. Introduction

Remotely sensed images (RSIs) are images captured by satellites and aerial imaging devices. Images of various locations on Earth taken by artificial satellites are called satellite images[1]. RSIs with high visualization are important for military reconnaissance and mapping, volcano prediction, ocean depth measurement, environment, and agriculture monitoring [2], [3]. Unfortunately, RSIs are often deteriorated due to low/high or uneven luminance, resulting in undesirable visualization [4], [5]. Different sun angles, at sensing time, result in different illumination values across the image. The nature of the sensed surfaces differs from type to another, leading to heterogeneity in RSI colors and intensity levels.

One of the most used image preprocessing techniques is contrast enhancement (CE), for low contrast images. One of the most popular and simple CE techniques is histogram equalization (HE) [6]. HE deteriorates the visual quality and introduces some undesirable artifacts on enhanced images[7]. There are a lot of histogram-based CE algorithms that aim to improve HE, using various approaches [8]–[14].

Since our eyes adapt to the local context of images to evaluate their contents, it makes sense to optimize local image contrast[15]. Adaptive Histogram equalization (AHE) achieves this by dividing the image into different contextual regions (CR). The noise problem associated with AHE can be mitigated by limiting contrast enhancement specifically in homogeneous areas. These areas can be characterized by a high peak in the histogram associated with the contextual regions[15]. Contrast limited Histogram Equalization (CLAHE) was found to avoid noise problems that resulted in AHE. CLAHE has produced good results on medical images [16].

Satellites are equipped with modern sensors that provide high-definition VHD images at various scales. The size of images differs from 1024*1024 to 4096*4096, which are considered very large images. Considering the images' large size and the heterogeneous nature of RSI, localized contrast enhancement techniques are more promising. However, techniques like AHE and CLAHE overcome the limitations of standard histogram equalization[15].

While CLAHE has shown favorable results in medical images, research on its use for RSIs is comparatively limited. To apply CLAHE effectively to heterogeneous RSIs, which are capturing various surfaces, different clip-limits are required to ensure optimal results. So, using CLAHE with a previously determined clip-limit has two major properties to consider; First, one clip-limit is applied for all contextual regions in a given image. Second, in each image, the best practice clip-limit should be selected that leads to the optimum result. Considering the static nature of clip-limit and the demonstrated nature of RSIs as an application domain, CLAHE is considered a not good competitor in CE of RSIs.

This paper proposes a dynamic method inspired by CLAHE. It aims to incorporate the best characteristics of CLAHE while introducing dynamic clip-limit HE. While the clip-limit serves as a hyperparameter in the CLAHE algorithm, it is unrelated to histogram characteristics. The introduced method analyzes the histogram of each contextual region (CR) and dynamically detects the most suitable clip-limit. Consequently, the proposed method offers improved image presentation, enhanced contrast, more locality, and better information preservation compared to CLAHE.

The main contributions of this study are:

1. **Elimination of Clip-Limit Hyperparameter**: Unlike CLAHE, which requires the specification of a clip-limit hyperparameter, our technique operates without the need for this parameter. This adjustment simplifies the user's experience and makes the method more accessible.
2. **Dynamic and Adaptive Clip-Limit**: While CLAHE applies a uniform clip-limit to all Contextual Regions (CRs) within an input image or segment of image, our technique takes a more sophisticated approach. It assigns a unique clip-limit to each CR but only when that CR contains outliers. This dynamic adaptation to individual CR makes our technique more responsive to image characteristics.
3. **Preservation of Information**: By not applying a global clip-limit to all CRs, and not clipping CRs that do not contain outliers, our approach preserves more information in the image. This preservation of information could increase the learning value.
4. **Enhanced Localization**: Our method goes beyond local histogram equalization by applying a calculated clip-limit specific to each CR. This localization ensures that adjustments are made precisely where they are needed, responding directly to the outliers within each CR.

In summary, the proposed technique represents a significant advancement over traditional CLAHE, offering improved adaptability, preservation of image content, and precise localization of enhancements. These contributions collectively make our approach a valuable addition to the field of image contrast enhancement.

This paper is organized as follows; Section 1 introduces the RSI contrast problems and recent solutions. Section 2 explains the recent related works for RSI CE problem and CLAHE recent research. Section 3 presents the proposed enhancements to the standard CLAHE. Section 4 presents the main assessment methods applied in this paper. Section 5 presents and discusses the result of the proposed method. Section 6 discusses proposed method and presents various results. Finally, Section 7 concludes the paper.

II. Related Work

In this section, recent RSI contrast enhancement methods are presented. State-of-the-art methods' results are not efficient enough as they could not offer better contrast, also unnatural looks, noise, artifacts, and local illumination problems are still challenges. Therefore, there are several recent research targets RSI image enhancements [17]–[19].

Several methods aimed to improve the traditional non-linear method General Histogram Equitization (GHE). Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE) was proposed [20]. Brightness Preserving Bi-Histogram Equalization (BBHE) and Dualistic Sub-Image Histogram Equalization (DSIHE) were proposed earlier to develop higher control over output image brightness. Recursive Mean Separate Histogram Equalization (RMSHE)[21] and Recursively Separated and Weighted Histogram Equalization (RSWHE)[22] were developed with the goal of enhancing contrast and mitigating the limitations of classical methods.

On the other hand, local contrast enhancement technique such as CLAHE[15] has the advantage of handling dark and bright areas within the image and preventing other areas within the image to be affected by them. It offers great results in the medical domain. In the medical domain, images like MRI, x-ray, or CT are homogeneous in morphological properties. On the contrary, RSIs have a heterogeneous characteristic in that one batch of sensed images could contain different surface types like the sea, agriculture space, rocket land, mountain, soil, and a combination of them. In this case, the nature of CLAHE could help in enhancing the contrast of different areas within the same image. Little research was found regarding enhancing CLAHE for remotely sensed images [9]–[14]

Up until recently, CLAHE was employed as a building block in different methods to make use of algorithm privileges, while some papers have aimed to optimize the clip-limit hyperparameter, they are comparatively fewer in number.

LCM-CLAHE was introduced, by Shelda et al, as a modified version of CLAHE that improved local contrast on the image using Local Contrast Modification (LCM) before sending it to CLAHE[23]. Huang Z et al, introduced CLAHE-DWT, which combined high frequency and improved low frequency layers by CLAHE to improve contrast in the low frequency layer of the DWT transformed image. Then reconstruct output using inverse DWT[24]. Laksmi et al, used CLAHE as a block following to wavelet transform in a novel approach [25]. Murat et al, Used CLAHE to improve the green channel of retinal pictures, Then the framework detects the optic disc proceeds.[26]. Ruizhi et al, calculated the clip-limit for the region of interest in ultrasound images, this approach used initial clip-limit imperially. It assumed five empirical gamma values as input for method γ-CLAHE. The optimal clip-limit is determined using the “contrast” metric. It did not consider the need for peak values to be suppressed. It also used one assessment metric [PSNR] as well as it conducted a limited number of trials to determine the ideal clip-limit.[27].

Centini et al, employed a supervised learning model to find a well-performing regression model. That is robust enough to predict the most promising CLAHE’s clip-limit to adjust an image based on its features. The aim of this method is to find best overall clip-limit to be used for all image [28]. Momoh et al, introduced LWT-CLAHE that used CLAHE and building block in proposed framework due to contrast enhancement capabilities [29]. Manju et al. employed CLAHE in the framework that was introduced by them. The framework utilized CLAHE's skills to improve illumination for dark images. [30]. Yakno et al, fused CLAHE and Fuzzy Adaptive Gamma to enhance Dorsal Hand Vein images [31].

Hameed et al, proposed IAECHE technique adaptively determines the optimal clip-limit for contrast enhancement. It detects peak values within sub-images (achieved via Quadric segmentation) and calculates their histogram entropy. However, it relies solely on entropy as a metric and applies one clip-limit to multiple contextual regions within the sub-image, determining peaks based on amplitude comparison to neighboring gray levels.[32]. Chakraverti et al, introduced DBST-LCM-CLAHE to determine the optimal block size by evaluating quality and re-enhance parameters within a denoising framework using deep learning approaches[33]. Lashkov et al, uses CLAHE in LAB color space for preprocessing low-light traffic camera images. It employs a dehazing technique to detect light sources, divides the image into tiles based on illumination, and sets a specific clip limit for each tile based on brightness[34]. Balakrishnan et al, employs CLAHE for contrast enhancement in the L channel of underwater images[35], Wang et al, utilizes CLAHE for dataset augmentation for better deep learning results[36].

All referenced papers primarily focus on learning or determining optimal clip-limit hyperparameter for input image or a segment of image, irrespective of its use within the algorithm. Our proposed method introduces a novel, low computation, block that automatically adapts to the intensity distribution of each contextual region (CR) and addresses outliers by applying suitable clipping. This innovative approach sets it apart from traditional CLAHE, a fact corroborated by our results and comparisons with standard CLAHE.

III. Proposed work

CLAHE is a technique employed for enhancing low contrast images. The process begins by 1) input image, 2) parameters insertion, two critical parameters, Block Size (BS) and Clip-Limit (CL), play a pivotal role. The Clip-Limit serves as a threshold, separating the histogram into two subsets: one for values below CL and another for values above CL. The cumulative count of pixel values exceeding the Clip-Limit is termed "Excesses". 3) dividing the input image into non-overlapping tiles known as Contextual Regions (CRs) based on BS size. For each CR, 4) a histogram is calculated. 5) CLAHE then clips the histogram to limit intensities and redistributes the “Excesses” across all intensity bins. Subsequently, 6) a standard histogram equalization process is applied to each CR. This entire sequence is repeated for all CRs, and finally, 7) the enhanced CRs are merged using bilinear interpolation to reconstruct the contrast-enhanced image. CLAHE's systematic approach enhances contrast adaptively, making it particularly useful for improving image visibility and preserving crucial details in low-contrast images. [15].

Figure 1 illustrates the proposed technique, which inherits most of its components from the CLAHE algorithm. Notably, the modifications are highlighted within the green blocks. Unlike the standard CLAHE approach, Block 2 in this technique doesn't require the initial insertion of the CL (Clip-Limit) parameter. Instead, this parameter is calculated dynamically in Block 7. Block 7 is introduced to compute outliers and make decisions accordingly. It determines whether to clip and distribute the excesses or pass them directly to Block 8.

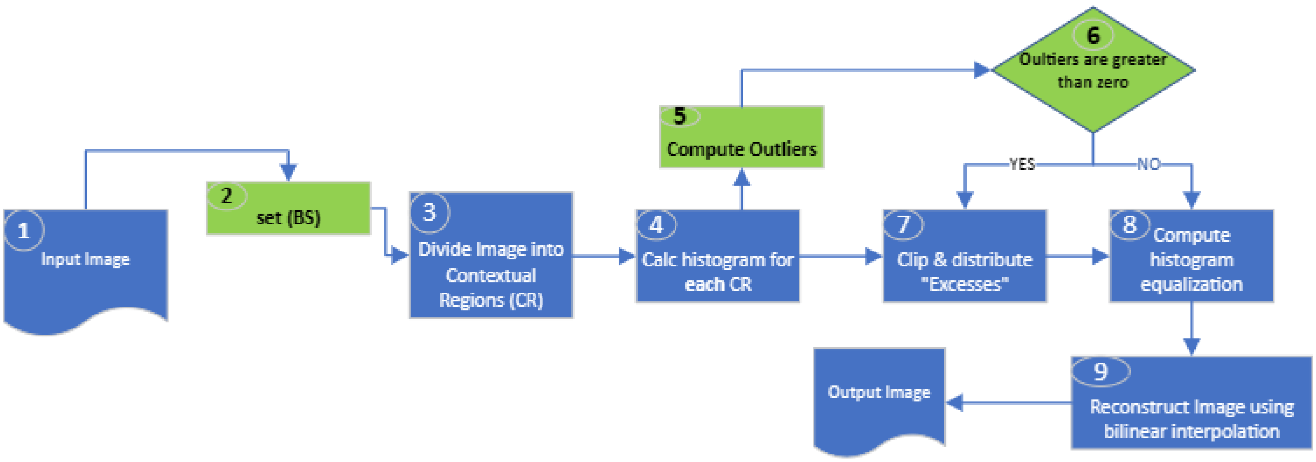

Fig. (1) Operational flow chart for proposed CLAHE

The default number of CRs is 64, extracted as 8 × 8 blocks [15] in the original implementation of the algorithm, while it was applied to medical images; however, it is widely used in this domain. In remote sensing images, the dimensions of the images, especially in the DOTA dataset used for this study, are larger in size. The CR dimension used in the conducted experiments is 32 x 32 pixels.

The proposed technique unfolds in a sequence of distinct stages, each contributing to its unique functionality and setting it apart from the classical CLAHE algorithm. The stages are as follows: 1) start with input image. 2) BS parameter is set to determine the size of CR. 3) divide image into non-overlapping CRs based on BS. 4) algorithm computes histogram for each CR. 5) it computes the outlier, IQR. 6) It switches between block 7 & 8 based on outlier existence. 7) In cases where outliers are identified, a sequence involving clipping excesses and redistributing pixel values is executed before transitioning to Block 8. 8) In scenarios where no outliers are detected or following the clipping and redistribution processes, histogram equalization is performed. 9) The equalized CRs are then subjected to bilinear interpolation to reconstruct the final enhanced image. Therefore, proposed method distinguishes itself from the classical CLAHE with respect to the following factors:

A. **Outlier Clip-Limit Detection Stage (block 5)**

In block 5, the algorithm computes histogram outlier. To identify outliers within the contextual region (CR) histogram, the algorithm employs the IQR method, a well-established mathematical technique for outlier detection.

The IQR method involves the computation of the first quartile (Q1) and the third quartile (Q3) of the data. Specifically, Q1 represents the mean of the values in the lower half of the data set, before the mean value, while Q3 represents the mean of the values in the upper half, after the mean value [37] The Interquartile Range (IQR) is then calculated using the Equation 1:

$$\mathrm{IQR} = \mathrm{Q3} - \mathrm{Q1} \tag{1}$$

It's important to note that the algorithm is designed to work with positive integer values only, and therefore, it calculates the upper boundary of the outlier values. This upper boundary, denoted as O, is determined by:

$$\mathrm{O} = \mathrm{Q3} + 1.5\ \mathrm{IQR} \qquad \forall\ \mathrm{O} \in \mathrm{N+} \tag{2}$$

Once the algorithm identifies the presence of outlier values in the CR histogram (i.e., when the count of outlier values is greater than zero), it proceeds to compute the adaptive clip-limit. This is achieved by calculating the Mean of the outlier values (Mo) using Equation 3, while n is count of intensities has outlier value, as well as the Mean of the histogram values without outlier values (Wo) using Equation 4. While $C(k)$ count of pixels in k intensity, W is count of intensities which has no outlier values. Finally, the adaptive clip-limit is determined as the sum of Mo and Wo, as illustrated in Equation 5

$$\mathrm{Mo} = \frac{\sum_{k=1}^{n} C(k)}{n} \tag{3}$$

$$\mathrm{Wo} = \frac{\sum_{k=1}^{w} C(k)}{w} \tag{4}$$

$$\text{Clip-limit} = \mathrm{Mo} + \mathrm{Wo} \tag{5}$$

B. **Histogram Clipping Stage (block 6 & 7)**

As figure 1 shows, the decision-making step (block 6) in flow chart. The algorithm uses computed IQR to determine whether to direct processing to Block 7 or Block 8 based due to the presence of outliers within the Contextual Region (CR). If outliers are detected, the algorithm is directed to (block 7) as it proceeds with the following steps:

1- Iterates through each gray level in the histogram and calculates a cumulative variable called 'excesses,' representing the number of pixels that exceed the clip-limit.
2- Sets the gray level to the minimum value between the original amount and the clip-limit.
3- Distribution: Iterates through the histogram and redistributes an equal number of pixels to each gray level until 'excesses' is exhausted.

If outliers are not present in the CR or Block 7 is processed, processing is directed to Block 8, where histogram equalization is performed. In the final step (Block 9), the algorithm reconstructs the enhanced image using bilinear interpolation.

In general, the proposed method addresses the static nature of the clip-limit through the introduction of a dynamic outlier-based detector that is calculated using the IQR method. This clip-limit is mathematically computed in each CR and will be set to zero for CR that has no outliers. This method dynamically avoids unnecessary clipping and iterative processes, resulting in improved information preservation. The results shown in the next section confirm this hypothesis.

IV. Evaluation Techniques

We evaluate the results using qualitative and quantitative analyses [38]to assess the robustness of the proposed method, which improves image brightness, and information preservation. Quantitative methods have two types as following:

A) **No-Reference Metrics**: These metrics include widely used measures such as discrete Entropy (DE) [39] which defines the richness of the image's structure. Higher values of DE indicate better definition and more details. Another essential metric is "contrast", which assesses the overall contrast of the images. A larger contrast value corresponds to higher overall image contrast [40], denoted by "con**"**. Additionally, Enhancement Measurement Error (EME) measures image quality [41].The higher EME the better image quality.

$$\mathrm{DE(X)} = -\sum_{k=1}^{k} p\left(x_k\right) log p\left(x_k\right) \tag{6}$$

$$\mathrm{con} = \frac{VAR}{\left[\frac{1}{MxN}\sum_{i=1}^{M}\sum_{i=1}^{N}\left(x(i,j)-\mu_x\right)^4\right]^{\frac{1}{4}}} \tag{7}$$

$$\mathrm{VAR} = \frac{1}{MxN}\sum_{i=1}^{M}\sum_{i=1}^{N}\left(x(i,j)-\mu_x\right)^2 \tag{8}$$

$$\mathrm{EME} = \frac{1}{k_1\, k_2}\sum_{l=1}^{k_2}\sum_{k=1}^{k_1}\frac{I_{max}(k,l)}{I_{min}(k,l)+c}\frac{I_{max}(k,l)}{I_{min}(k,l)+c} \tag{9}$$

Wherein, $p\left(x_k\right)$ is the probability associated with pixel value x_k, K is a gray level form Image X, M and N correspond to the height and width, μ_x is the mean of the image, "Var" stands for variance. k_1 represents the number of blocks in height dimension while k_2 relates to the number of blocks in width dimension. I_{max} signifies the maximum value within the block, I_{min} the minimum value within the block. The blocks used are of size 8×8. The blocks with I_{min} were neglected, to avoid division by zero, rather than using small constant c in equation 9.

B) **Reference Metrics**: That have been widely used in remote sensing research; Contrast Gain (CG) [9], which defines the degree of local contrast achieved in comparison to the original image, also called Michelson contrast. The more CG is, the better contrast enhancement. Peak Signal to Noise Ratio (PSNR) defines the quality of the image by a higher rank with respect to the original. Absolute mean brightness error (AMBE) measures the error in brightness [42]; the smaller the AMBE is, the better the brightness preservation.

$$\mathrm{PSNR} = 10\times \lg lg\, \frac{L\times L}{MSE} \tag{10}$$

$$\mathrm{MSE} = \frac{\sum_{0\le J\le N}^{N}\sum_{0\le I\le M}^{M}\left(X_{ij}-Y_{ij}\right)^2}{M\times N} \tag{11}$$

Wherein, L denotes grayscale levels. MSE represents the mean square error, with X and Y representing the input image and output image, respectively. M and N denote the height and width, respectively.

$$\mathrm{CG} = \mathrm{C}(Y)/\mathrm{C}(X) \tag{12}$$

$$C_{michelson} = \frac{MAX-MIN}{MAX+MIN} \tag{13}$$

Where C represents local contrast of block in image Y or X, calculated using $C_{michelson}$ for a block size of 3 x 3 pixel window. If (max + min = zero) block value is neglected to avoid division by zero.

$$\mathrm{AMBE\ (x,y)} = |\mu_x - \mu_y| \tag{14}$$

For images x and y, μ_x represents the mean of the input image, and μ_y related to the mean of the output image. Moreover, another performance evaluation metrics are used.

Information Preservation:

Contrast enhancement techniques are, by definition, lossy techniques. Therefore, there is a trade-off involving the loss of information in exchange for improved contrast. This loss of information happens while CLAHE redistributes “Excesses” across all levels of the contextual region (CR) histogram in consideration to the given clip-limit. Consequently, the less “Excesses” are clipped, the more information is retained from alteration. This, in turn, enhances the probability of preserving the original image details in the output image.
The CR clipping nature of the proposed algorithm is evaluated based on two criteria: the first criterion is the number of CRs that have been clipped, and the second is the number of intensities that have been redistributed (Excesses). The Percentage of Saved Excesses (PSE) serves as a metric and is calculated as follows:

$$PSE = 100 - \text{Excesses of Proposed} / \text{Excesses of CLAHE} \quad (15)$$

A qualitative assessment was applied too in this study. Next section presents the experiments results and comparisons to standard CLAHE.

V. Experimental Results

A. Dataset Description and Selection

In this paper, DOTA dataset is utilized for our experiments [43]. The DOTA images are collected from various sources, including Google Earth, GF-2, and JL-1 satellite provided by the China Centre for Resources Satellite Data and Application, and aerial images provided by CycloMedia B. V[44]. DOTA has been cited widely in remotely sensed papers[45], [46]. The sizes of images vary from 1024x1024 to 4096x4096 pixels, making them considerably large images.

B. Dataset preprocessing

For the selection process, the DOTA RSI dataset was scanned randomly using the “contrast” metric (4) to identify low-intensity Images. The scan was conducted on 272 randomly selected images. A “contrast” threshold was set to 21. Therefore, images with a “contrast” score below this threshold were categorized as low-contrast images, resulting in a total of ninety-eight identified images. The experiments were conducted using Python 3.9, various libraries, an 8th-generation Intel Core i7 processor, and 12 gigabytes of RAM.

C. Information Preservation

In this subsection, the evaluation of preserving the information in RSI images is presented. The proposed method is compared to the original CLAHE clipping approach, and the results are shown in Table 1. Since clip-limit is an essential parameter in CLAHE, we applied CLAHE using various clip-limits, namely [1.5, 2, 2.5, 3 and 3.5].

Table (1) CR affected by different techniques.

Technique	**Clip-limit**	**average of clipped excesses**	**PSE**
CLAHE	1.5	16,722	**56%**
CLAHE	2	14,700	**50%**
CLAHE	2.5	12,978	**43%**
CLAHE	3	11,514	**36%**
CLAHE	3.5	10,282	**28%**
Proposed	-	**7,399**	-

In total, 6272 CRs belonging to the ninety-eight selected images were processed. CLAHE clipped 100% of CRs across all tested clip-limits. In contrast, the proposed method applied clipping on only 92% of CRs. The “Excesses” is the number of intensities lying above the clip limit. “Excesses” represent the number of intensities exceeding the clip-limit, indicating the pixels that need to be redistributed to other intensities. Since pixels hold information, redistributing them on other Intensities constitutes a form of information alteration, aimed at achieving better contrast. Therefore, the fewer “Excesses” are redistributed, the more information is preserved. The proposed method demonstrates its ability to distinguish automatically which CRs need to be clipped, and its “Excesses” be distributed across quantization range, due to CR detected outliers.

In Table 1, the first column indicates the technique used, while the second column displays the clip-limit applied in the case of CLAHE. The third column labeled 'Excesses' represents the average pixels count that were redistributed in each contextual region (CR). The last column presents the Percentage of Saved Excesses (PSE), calculated using Equation 15. PSE represents the saving ratio in excess pixels count when our proposed method is applied instead of CLAHE.

Table 1 demonstrates that the proposed method excels in preserving information in RSIs compared to CLAHE, with PSE ratios ranging from 28% to 56%. The proposed method exhibits the ability to dynamically determine which CRs require clipping, and the extent of clipping required.

Figure 2 displays a sample CR histogram before and after applying clipping using both the proposed method and CLAHE with varying clip-limits. As the CR does not contain outliers, the proposed algorithm (g) successfully preserves the entire CR histogram's data. In contrast, applying CLAHE with different clip limits leads to information clipping. This highlights the proposed method's capability to mathematically and dynamically assess whether clipping is necessary for the CR.

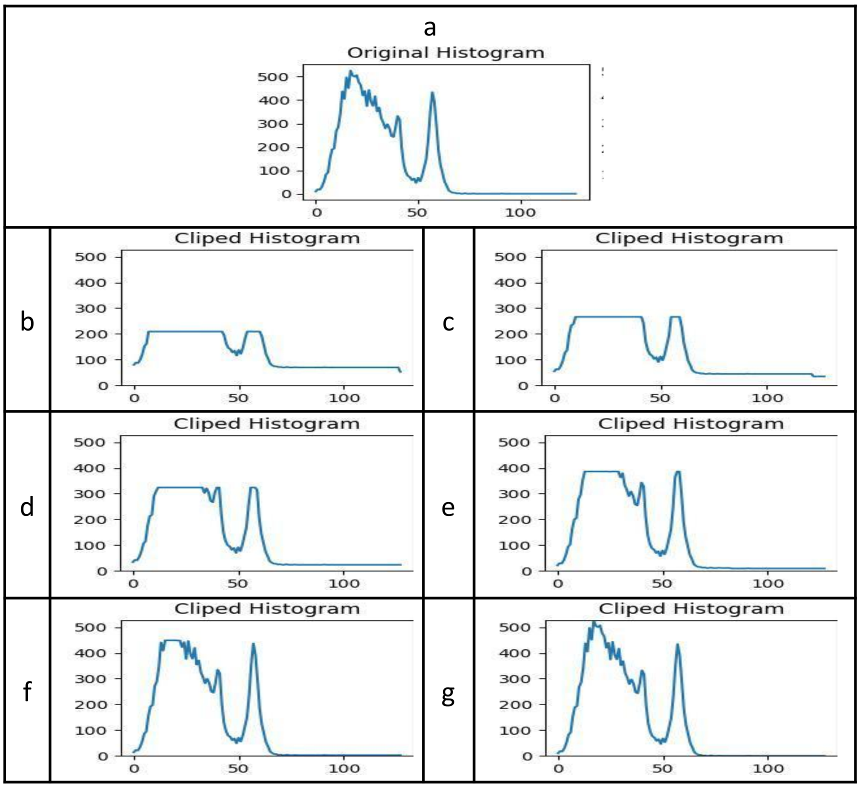

Fig. (2) CR Histogram after applying clipping a) Original histogram before clipping, (b to f) CLAHE on clip limits 1.5,2,2.5,3,3.5 respectively and g) proposed.

D. **Quantitative Assessment**

Table 2 shows the average results of the proposed technique compared to CLAHE using no-reference metrics. The average of original is 16.352, 25.325 and 6.457 for contrast, EME and DE respectively. In reference to CLAHE, the first column represents “contrast” Metric. consistently outperforms all tested clip-limits of CLAHE in terms of the 'contrast' metric. Regarding EME, the proposed algorithm surpasses CLAHE for all different applied clip-limits, achieving nearly double the enhancement compared to CLAHE. The enhancement over the original score is almost tenfold. Additionally, DE, the widely used in RSI research comparisons, also yields better results with the proposed technique than with CLAHE.

As demonstrated by numerical values, the proposed technique outperforms conventional CLAHE across all no-reference metrics over a wide range. Notably, this assessment considered various Clip-Limits as hyperparameters for classic CLAHE, while the proposed technique operates without the need for such parameter. Consequently, the proposed technique exhibits greater autonomy and achieves superior performance across this range of metrics.

Table (2) No-Reference Metrics average results.

Techniques	Contrast	EME	DE
Proposed	48.891	223.412	7.788
CLAHE (1.5)	24.186	44.804	6.947
CLAHE (2)	29.334	63.039	7.19
CLAHE (2.5)	33.942	82.155	7.368
CLAHE (3)	37.917	108.807	7.498
CLAHE (3.5)	41.255	137.766	7.593

Table 3 reveals slight improvements in PSNR and AMBE, albeit with a noticeable increase in AMBE when compared to classical CLAHE. Visual results demonstrate enhanced detail visibility and improved treatment of both very dark and very bright areas within the image, while maintaining a natural appearance.

Table (3) Reference Metrics results

Technique	PSNR	CG	AMBE
Proposed	27.960	3.271	35.196
CLAHE (1.5)	29.478	1.465	10.352
CLAHE (2)	28.691	1.745	15.801
CLAHE (2.5)	28.378	2.027	20.383
CLAHE (3)	28.207	2.290	24.248
CLAHE (3.5)	28.117	2.528	27.451

E. Qualitative Assessment

While defined metrics are beneficial to discriminate images, they alone may not provide a comprehensive assessment of a technique's performance. Therefore, it is necessary to combine subjective evaluation with quantitative evaluation in this research. Briefly, if the visual look of an image is poor, it will be determined to be poor regardless of the values of the other quantity indexes[19].

To assess the proposed algorithm performance on satellite images, the selected dataset images were enhanced using commonly used global contrast enhancement techniques ('GHE', 'RMSHE', 'DSIHE', 'BBHE', 'MMBEBHE', 'RSWHE' and 'AGCWD'). Since CLAHE results are affected by the clip-limit set by the user, different five clip-limits were implemented [1.5, 2, 2.5, 3 and 3.5]. This was done to demonstrate the visual effect of different clip-limits on the result of CLAHE enhancement comparing to remote sensing images state-of-the-art.

Since the images used in the experiment are too large display in their entirety alongside the results of state-of-the-art methods, a portion of the image, sized by 512 × 512 pixels, is showcased in Figure 3, This figure illustrates the contrast enhancement performed on the image using CLAHE with different five inputs from 1 to 3.5, the original image, and the output of the proposed method. Notably, the proposed method reveals more details than all other CLAHE outputs. In the proposed method outcome, details of image are unaffected, especially in bright areas.

Because those images depend mainly on passive sensing, image illumination is highly influenced by the angle of sun light. When the sun is at a low angle, the image may suffer from poor illumination, and conversely, when the sun is at a higher angle, illumination improves. As illustrated in Figure 2, this approach can yield greater details and enhance overall image brightness.

To visually highlight the distinction between global equalization and local equalization, Figure 4 displays the outputs of various global histogram equalization techniques applied to the same sample image used in Figure 3.

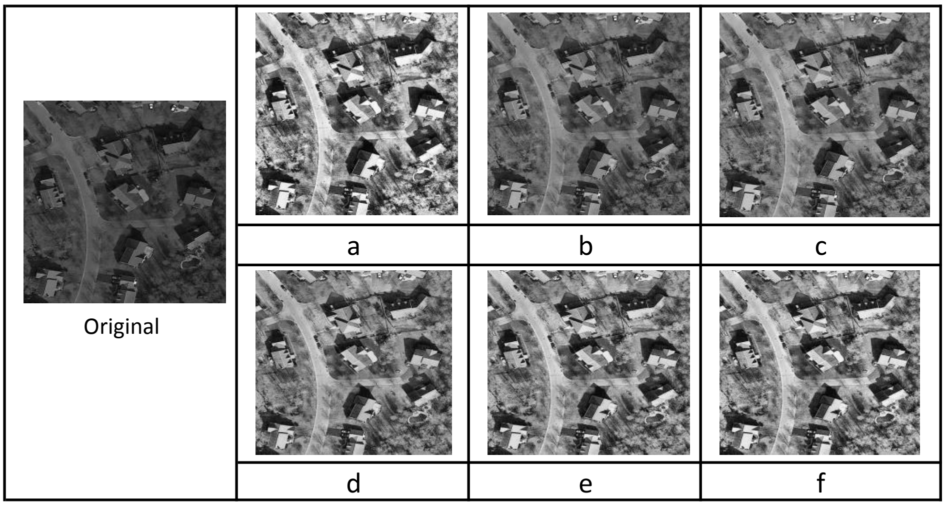

Fig. (3) Original low contrasted image and the enhanced output images using, a) the proposed method and (b-f) CLAHE with clip limits [1.5,2,2.5,3 and 3.5] in order.

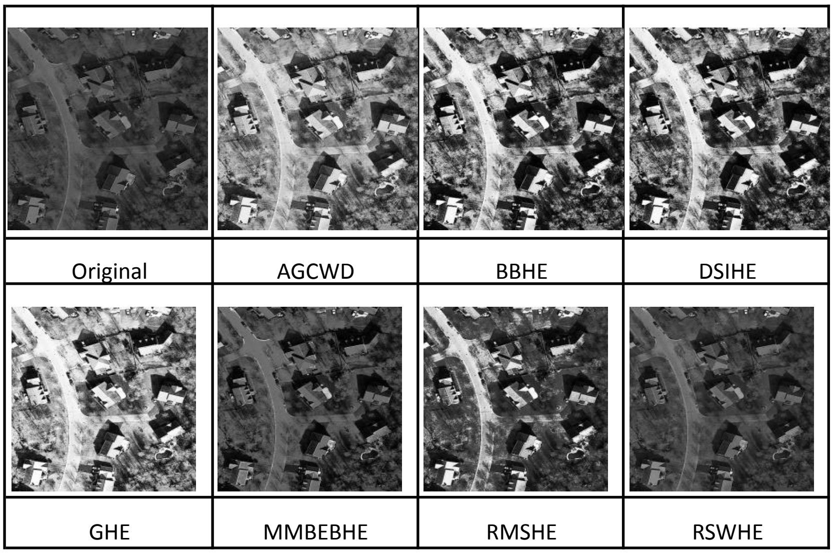

Fig. (4) Global CE Techniques output images

In Figure 4, the techniques MMBEBHE and RSWHE exhibited limited contrast enhancement while preserving illumination levels close to the original image. RMSHE produced better-looking images but tended to darken areas rich in details. BBHE and DSIHE introduced more darkness in regions having more details. GHE resulted in an over-contrasted image and brighter areas. And AGCWD showed less contrast effect than others.

While AMBE is used to measure brightness change, by visual notice, the elevation in brightness does not result in contrast and it does not affect the details or the texture of the image. It maintained the natural look and avoided the artifacts in the output image. Even it could be added as virtue like in this proposed method[47].

F. **Discussion**

Histograms serve as powerful tools for visually representing intensity and contrast level distributions in images. Figure 5 displays the histogram of the original sample image and state-of-art global contrast enhancement methods. Figure 6 shows the histogram of CLAHE, and the proposed method applied to the same image.

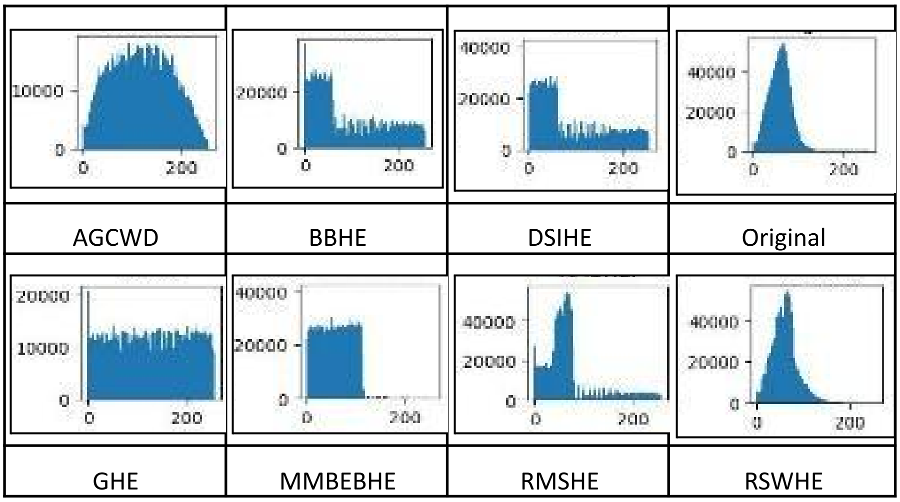

Fig. (5) Original Image Histogram and Enhanced state-of-art techniques histograms

Figures 6 and 7 vividly portray the primary issue of narrow intensity representation that contributes to contrast problems in the original image. The results obtained from techniques [MMBEBHE, RMSHE, RSWHE, BBHE, DSIHE] reveal that the intensities remain concentrated in a narrow range of quantization. On the other hand, GHE and AGCWD exhibit a spreading of intensities over the full range of quantization. While GHE seems to give equal probabilities to the occurrence of intensities, AGCWD offers a more normal distribution with smaller probability towards end of quantization range.

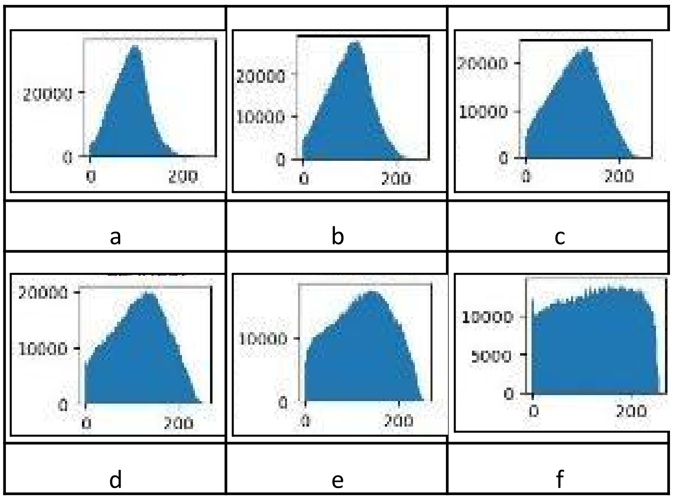

Fig. (6) CLAHE enhanced histograms for different clip-limit from (a-f) for limits [1.5,2,2.5,3,3.5] and proposed method in order

CLAHE results in a shift in intensities probability towards darker areas and, the probability of gray levels decreases in the middle of the range, proportionally to the increase in pre-set clip-limit. The proposed method, however, showcases a full quantization distribution for the original intensities. Which clearly demonstrates the success in enhancing localization in produced image. It can control peaks and offers optimum distribution. This effectiveness is clearly visible through the histogram compact and continuous.

Despite the clear superiority of the proposed algorithm over the classic CLAHE, it's important to recognize that digital assessment serves as a complementary description [19]. In conclusion, the results unequivocally demonstrate that the proposed method excels not only in effectively enhancing image contrast and overall image quality, preserving finer details, and preventing unnecessary loss of information but also in maintaining the complexity, as illustrated in Figure 7[19]

(a) (b)

Fig. (7) A high resolution sample image (a) the original low contrasted image, (b) the enhanced image by the proposal method

Local contrast methods can improve the details in the considered image and preserve the image's naturalness.[48], [49] This focus on localized contrast enhancement sets them apart from other contrast enhancement techniques, which do not offer these benefits. HE often produces undesirable artifacts and dramatically changes the character of the image[50], [51]. Moreover, HE often makes some of the uniform regions become saturated with a very bright or dark look[19]. Table 4 offers a quantitative assessment that highlights elevated Contrast Gain (CG) and Peak Signal-to-Noise Ratio (PSNR) values associated with specific state-of-the-art techniques. These findings hint at a potential issue of over-contrast in the processed images. It is important to note that our research did not yield a definitive threshold, in metrics numbers, that identifies the over-contrast case. Nevertheless, as supported by multiple references, a comprehensive approach that combines both visual evaluation and numerical analysis could provide a more thorough understanding of this issue. For instance, Figure 4 depicts an image processed using RSWHE, revealing a noticeable lack of visual contrast. This observation is further substantiated by the histogram displayed in Figure 5, which shows an accumulation of pixel intensities in the lower range. In contrast, DSIHE achieves the highest CG, but exhibits noticeable artifacts in the upper-right dark corner, as evident in Figure 4. Also, the corresponding histogram in Figure 5, for same image, confirms the uneven distribution of pixel intensities in the same image.

Table (4) global contrast techniques and proposed numerical results.

Technique	PSNR	Contrast Gain
Proposed	27.96	3.271
DSIHE	28.1	3.928
BBHE	28.15	3.835
MMBEBHE	28.31	3.371
RMSHE	31.82	2.538
RSWHE	35.69	1.278
AGCWD	27.62	1.485
GHE	28.03	3.467

When evaluating performance independently, complexity plays a pivotal role. Contrast Limited Adaptive Histogram Equalization (CLAHE) is characterized by a complexity of O (n^2). Considering that the introduced technique corporates new block to CLAHE, it requires an increased computational demand, due to outlier and clip-limit computation. However, those operations are linear equation with complexity O (n). However, the proposed technique mitigates this increased computational cost by reducing the need, as implemented on used dataset, for clipping in 8% of the contextual regions (CRs) and reducing excesses from 28% to 56% in used dataset, as indicated in Table 1. This trade-off allows proposed algorithm to achieve better image quality while incurring a reasonable computation cost.

CLAHE is effective, well-established, and still in use in many domains. When it comes to selecting the most suitable clip-limit, numerous research endeavors have explored different methods. However, the proposed technique offers an intrinsic mechanism for computing the clip-limit. This internal block effectively removes the necessity of employing an external algorithm to determine or learn the optimal clip-limit. Consequently, this not only reduces the overall computational workload but also enhances the autonomy and contrast enhancement localization of the algorithm.

VI. Conclusion

This study presents an automated adaptive contrast enhancement technique designed for remotely sensed images. Building upon the conventional CLAHE technique, the proposed approach incorporates an automatic clip-limit detection block for each contextual region. This addition aims to enhance local contrast and preserve image details effectively. The evaluation conducted using the DOTA dataset yielded favorable quantitative results, demonstrating the superiority of the proposed technique over standard CLAHE in terms of localized contrast, global contrast, discrete definition, and details preservation. Qualitative analysis further confirmed the enhanced visualization capabilities of the proposed technique compared to both state-of-the-art methods and the primary CLAHE. It also exhibited robustness across various scenarios. The results highlighted the method's dynamic and adaptive nature, which contributed to improved information preservation. Notably, the proposed approach offers greater autonomy by eliminating the need for a clip-limit hyperparameter and achieves enhanced localization through responsive clip-limit adaptation for each contextual region. Remarkably, this enhanced capability comes with comparable or even reduced complexity compared to classic CLAHE. Thus, the proposed technique offers a practical solution for autonomous local contrast enhancement in remotely sensed images, with potential applications in the field of medical imaging. Future research avenues could explore ways to further reduce algorithm complexity, possibly through the adoption of improved interpolation algorithms.

References

[1] L. Sharma, S. Sengupta, and B. Kumar, “An improved technique for enhancement of satellite image,” in *Journal of Physics: Conference Series*, IOP Publishing Ltd, Jan. 2021, p. 012051. doi: 10.1088/1742-6596/1714/1/012051.

[2] Z. Huang *et al.*, “Unidirectional variation and deep CNN denoiser priors for simultaneously destriping and denoising optical remote sensing images,” *Int J Remote Sens*, vol. 40, no. 15, pp. 5737–5748, 2019.

[3] Z. Huang *et al.*, “Joint analysis and weighted synthesis sparsity priors for simultaneous denoising and destriping optical remote sensing images,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 58, no. 10, pp. 6958–6982, 2020.

[4] Z. Huang, Y. Zhang, Q. Li, T. Zhang, N. Sang, and H. Hong, “Progressive dual-domain filter for enhancing and denoising optical remote-sensing images,” *IEEE Geoscience and Remote Sensing Letters*, vol. 15, no. 5, pp. 759–763, 2018.

[5] W. Cao, Y. Chang, G. Han, and J. Li, “Destriping remote sensing image via low-rank approximation and nonlocal total variation,” *IEEE Geoscience and Remote Sensing Letters*, vol. 15, no. 6, pp. 848–852, 2018.

[6] R. C. Gonzale and R. E. Wood, *Digital Image Processing, 3rd ed.* NJ: Pearson Education, 2010.

[7] J. Lee, S. R. Pant, and H.-S. Lee, “An adaptive histogram equalization based local technique for contrast preserving image enhancement,” *International Journal of Fuzzy Logic and Intelligent Systems*, vol. 15, no. 1, pp. 35–44, 2015.

[8] J. Shin and R.-H. Park, "Histogram-based locality-preserving contrast enhancement," *IEEE Signal Process Lett*, vol. 22, no. 9, pp. 1293–1296, 2015.
[9] X. Fu, J. Wang, D. Zeng, Y. Huang, and X. Ding, "Remote sensing image enhancement using regularized-histogram equalization and DCT," *IEEE Geoscience and Remote Sensing Letters*, vol. 12, no. 11, pp. 2301–2305, 2015.
[10] J. Ho, S. D. Kim, and J. B. J. Ra, "Enhancement of Optical Remote Sensing Images by Subband-Decomposed Multiscale Retinex With Hybrid Intensity Transfer Func," *IEEE Geoscience and Remote Sensing Letters*, vol. 8, no. 5, pp. 983–987, 2011.
[11] S. Saleh, N. V Kalyankar, and S. D. A.-A. Khamitkar, "Contrast stretching enhancement in remote sensing image," *International Journal of Computer Science Issues (IJCSI)*, vol. 7, no. 2, p. 26, 2010.
[12] K. Mohd Farhan, E. Khan, and A. Z. A., *Multi Segment Histogram Equalization for Brightness Preserving Contrast Enhancement*. Springer, 2012.
[13] B. Kriti and S. Rishi, "Analysis of Image Enhancement Techniques Used in Remote Sensing Satellite Imagery," *Int J Comput Appl*, vol. 975, p. 8887, 2017.
[14] H. Demirel, C. Ozcinar, and G. Anbarjafari, "Satellite Image Contrast Enhancement Using Discrete Wavelet Transform and Singular Value Decomposition," *IEEE Geoscience and remote sensing letters*, vol. 7, no. 2, pp. 333–337, 2009.
[15] K. Zuiderveld, *Contrast Limited Adaptive Histogram Equalization*. Elsevier, 1994.
[16] A. M. Reza, "Realization of the contrast limited adaptive histogram equalization (CLAHE) for real-time image enhancement," *J VLSI Signal Process Syst Signal Image Video Technol*, vol. 38, pp. 35–44, 2004.
[17] Z. Huang, Z. Wang, J. Zhang, Q. Li, and Y. Shi, "Image enhancement with the preservation of brightness and structures by employing contrast limited dynamic quadri-histogram equalization," *Optik (Stuttg)*, vol. 226, p. 165877, 2021.
[18] Z. Huang *et al.*, "Luminance learning for remotely sensed image enhancement guided by weighted least squares," *IEEE Geoscience and Remote Sensing Letters*, vol. 19, pp. 1–5, 2021.
[19] J. Liu, C. Zhou, P. Chen, and C. Kang, "An efficient contrast enhancement method for remote sensing images," *IEEE Geoscience and Remote Sensing Letters*, vol. 14, no. 10, pp. 1715–1719, 2017.
[20] S.-D. Chen and A. R. Ramli, "Minimum mean brightness error bi-histogram equalization in contrast enhancement," *IEEE transactions on Consumer Electronics*, vol. 49, no. 4, pp. 1310–1319, 2003.
[21] S.-D. Chen and A. R. Ramli, "Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation," *IEEE Transactions on consumer Electronics*, vol. 49, no. 4, pp. 1301–1309, 2003.
[22] M. Kim and M. G. Chung, "Recursively separated and weighted histogram equalization for brightness preservation and contrast enhancement," *IEEE Transactions on Consumer Electronics*, vol. 54, no. 3, pp. 1389–1397, 2008.
[23] S. Mohan and M. Ravishankar, *Modified contrast limited adaptive histogram equalization based on local contrast enhancement for mammogram images*. Springer, 2013.
[24] H. Lidong, Z. Wei, W. Jun, and S. Zebin, "Combination of contrast limited adaptive histogram equalisation and discrete wavelet transform for image enhancement," *IET Image Process*, vol. 9, no. 10, pp. 908–915, 2015.
[25] T. V Laksmi, T. Madhu, K. Kavya, and S. E. Basha, "Novel image enhancement technique using CLAHE and wavelet transforms," *International Journal of Scientific Engineering and Technology*, vol. 5, no. 11, pp. 507–511, 2016.
[26] H. Murat, kver Yunus, E. Duman, and O. A. nver Erdem, "Statistical edge detection and circular hough transform for optic disk localization," *Applied Sciences*, vol. 9, p. 350, 2019.
[27] R. Zheng, Q. Guo, C. Gao, and M. Yu, *A Hybrid Contrast Limited Adaptive Histogram Equalization (CLAHE) for Parathyroid Ultrasonic Image Enhancement*. 2019.
[28] G. F. Centini, S. M. Mastelini, G. J. Aguiar, R. G. Mantovani, L. F. de Melo, and S. C. Barbon, "Machine learning hyperparameter selection for contrast limited adaptive histogram equalization," *EURASIP J Image Video Process*, pp. 1–18, 2019.
[29] M. O. Momoh, "LWT-CLAHE Based Color Image Enhancement Technique: An Improved Design," *omputer Engineering and Applications Journal*, vol. 9, no. 2, pp. 117–126, 2020.
[30] R. Manju, G. Koshy, and P. Simon, "Improved Method for Enhancing Dark Images based on CLAHE and Morphological Reconstruction," *Procedia Comput Sci*, vol. 165, pp. 391–398, 2019.

[31] M. Yakno, J. Mohamad-Saleh, and M. Z. Ibrahim, “Dorsal Hand Vein Image Enhancement Using Fusion of CLAHE and Fuzzy Adaptive Gamma,” *Sensors*, vol. 21, p. 6445, 2021.

[32] S. H. Majeed and N. A. M. Isa, “Iterated adaptive entropy-clip limit histogram equalization for poor contrast images,” *IEEE Access*, vol. 8, pp. 144218–144245, 2020.

[33] S. Chakraverti, P. Agarwal, H. S. Pattanayak, S. P. S. Chauhan, A. K. Chakraverti, and M. Kumar, “De-noising the image using DBST-LCM-CLAHE: A deep learning approach,” *Multimed Tools Appl*, pp. 1–26, 2023.

[34] I. Lashkov, R. Yuan, and G. Zhang, “Edge-Computing-Facilitated Nighttime Vehicle Detection Investigations With CLAHE-Enhanced Images,” *IEEE Transactions on Intelligent Transportation Systems*, 2023.

[35] A. A. Balakrishnan, P. Dhanya, S. Anilkumar, and M. Supriya, “A Novel L-CLAHE-Based Intensification Filter for Enhancement of Underwater Images and Pipeline Tracking,” *IETE J Res*, pp. 1–10, 2023.

[36] X. Wang, T. Wang, and J. Li, “Advanced crack detection and quantification strategy based on CLAHE enhanced DeepLabv3+,” *Eng Appl Artif Intell*, vol. 126, p. 106880, 2023.

[37] H. Perez and J. H. M. Tah, “Improving the accuracy of convolutional neural networks by identifying and removing outlier images in datasets using t-SNE,” *Mathematics*, vol. 8, no. 5, p. 662, 2020.

[38] R. Atta and M. Ghanbari, “Low-contrast satellite images enhancement using discrete cosine transform pyramid and singular value decomposition,” *IET Image Process*, vol. 7, no. 5, pp. 472–483, 2013.

[39] H. Liu, S. Liu, T. Huang, Z. Zhang, Y. Hu, and T. Zhang, “Infrared spectrum blind deconvolution algorithm via learned dictionaries and sparse representation,” *Appl Opt*, vol. 55, no. 10, pp. 2813–2818, 2016.

[40] L. Liu, Z. Jia, J. Yang, and N. Kasabov, “A remote sensing image enhancement method using mean filter and unsharp masking in non-subsampled contourlet transform domain,” *Transactions of the Institute of Measurement and Control*, vol. 39, no. 2, pp. 183–193, 2017.

[41] E. Lee, S. Kim, W. Kang, D. Seo, and J. Paik, “Contrast enhancement using dominant brightness level analysis and adaptive intensity transformation for remote sensing images,” *IEEE Geoscience and remote sensing letters*, vol. 10, no. 1, pp. 62–66, 2012.

[42] Z. Huang, T. Zhang, Q. Li, and H. Fang, “Adaptive gamma correction based on cumulative histogram for enhancing near-infrared images,” *Infrared Phys Technol*, vol. 79, pp. 205–215, 2016.

[43] “https://captain-whu.github.io/DOTA/dataset.html, access time 18 September 2023 6:00 pm”

[44] “https://paperswithcode.com/dataset/dota, access time 18 September 2023 6:00 pm”

[45] P. Zhen *et al.*, “Towards accurate oriented object detection in aerial images with adaptive multi-level feature fusion,” *ACM Transactions on Multimedia Computing, Communications and Applications*, vol. 19, no. 1, pp. 1–22, 2023.

[46] Q. Ming, L. Miao, Z. Zhou, J. Song, Y. Dong, and X. Yang, “Task interleaving and orientation estimation for high-precision oriented object detection in aerial images,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 196, pp. 241–255, 2023.

[47] L. Hu, M. Qin, F. Zhang, Z. Du, and R. Liu, “RSCNN: a CNN-based method to enhance low-light remote-sensing images,” *Remote Sens (Basel)*, vol. 13, no. 1, p. 62, 2020.

[48] Q.-C. Tian and L. D. Cohen, “Global and local contrast adaptive enhancement for non-uniform illumination color images,” in *Proceedings of the IEEE International Conference on Computer Vision Workshops*, 2017, pp. 3023–3030.

[49] J. A. Stark, “Adaptive image contrast enhancement using generalizations of histogram equalization,” *IEEE Transactions on image processing*, vol. 9, no. 5, pp. 889–896, 2000.

[50] Shih-Chia, F.-C. Cheng, and Y.-S. H. Chiu, “Efficient Contrast Enhancement Using Adaptive Gamma Correction With Weighting Distribution,” *IEEE transactions on image processing*, vol. 22, no. 3, pp. 1032–1041, 2012.

[51] Q. Wang and R. K. Ward, “Fast image/video contrast enhancement based on weighted thresholded histogram equalization,” *IEEE transactions on Consumer Electronics*, vol. 53, no. 2, pp. 757–764, 2007.