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Dynamic Clip Limit Window Size Histogram Equalization for Poor Information Images

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Abstract: During the image enhancement process, hidden information, poor capturing device quality lead to poor image contrast, insufficient user experience, and an inappropriate data collecting environment setting have all been noted as serious concerns. Histogram equalization techniques have been used to solve the challenges described above. Nonetheless, the images obtained using these methods are frequently impacted by unwanted artifacts, and unnatural appearances effects. Due to that, this research presented a novel strategy for enhancing contrast called Dynamic Clip Limit Window Size Histogram Equalization. The proposed technique uses a new fitness function of combining the discrete entropy and root mean square error parameters. The proposed strategy's qualitative and quantitative result is validated and assessed against 5 state-of-the-art strategies (HSQHE, ACLTSHE, CLAHE, AEIHE, and IAECHE). The proposed technique proved its high capability to produce the best average DE, CII, and SSI values for the Faces-199 dataset (7.869, 1.000, and 0.999, respectively).

Keywords: Histogram, Clip-limit, Window size, Optimization, Histogram equalization.

1. Introduction

Various image capture products, such as security cameras, cameras, and mobile phones, produced in the previous years and are widely utilized by people for private, documentary, scientific, medical, as well as satellite aplications. However, the images quality obtained by those products remain subjective and is determined by various factors, including camera lens quality, lighting, and user experience. On this basis, inadequate lighting, contrast, and noise in image can all affect image quality. Thus, image enhancement is a crucial process in the image processing field, including image segmentation, feature extraction, and classification [1]. Accordingly, image enhancement techniques are used to increase the appearance, enhance the details, and improve the contrast of images [2]. Contrast enhancement techniques are classified into two domains, namely, the spatial and frequency domains. Techniques in the frequency domain use transform techniques, transform images from the spatial domain to the frequency domain, and then compute the transform coefficients, manipulate the computed coefficients, and finally return the manipulated image to the spatial domain [3]. Spatial domain techniques manipulate the image information directly without converting it to another domain.

This study was inspired by the aforementioned issue to offer a new LHE-based contrast enhancement technique. The proposed research aims to improve the input image's information richness and highlight local characteristics. Despite the fact that The proposed strategy is within the LHE category, and it will ensure that the contrast is even or uniform over the full set of images. This will eliminate the first problem described before. To address the second issue, the proposed method would employ an approach that will automatically and adaptively set all parameters. By removing the subjective impacts of users, this method will have a more concrete contrast enhancement technique. Furthermore, in the proposed technique, to enhance the local details of images without introducing undesirable noise or wash-out phenomena, a novel approach to local augmentation will be presented..

The rest of this study is structured as follows: Section 2 reviews the histogram equalization and various of its derived techniques. Section 3 presents the methodology of the proposed work. Section 4 illustrates the datasets and the evaluation metrics. Section 5 illustrates the results and discussion of the proposed technique. The conclusion of the work is presented in Section 6.

2. Histogram equalization

One of the famous techniques is histogram equalization (HE), which increases the imparity between the background and the foreground of images. Furthermore, HE redistributes the intensity of images in a uniform approach over the entire gray levels to improve their contrast [4]. This technique is widely applied in real-time and tracking systems for its simplicity and minimal time requirement. However, the HE technique has some limitations, such as its poor capability to maintain the details of the original input. In addition, the final images are washed out due to the shift of the image's mean value [5]. To avoid the limitations of the HE technique, researchers developed various techniques based on HE. The techniques derived from HE could be classified into several groups depending on the manipulation of the image intensity, namely, dividing the original histogram to be two sub-histograms, dividing the histogram into sub-histograms, modifying the image's histogram, dividing the image into small blocks, and exposing the regions of the histogram. These groups are referred to as bi sub-imaging histogram equalization (BSHE), multiple sub-imaging histogram equalization (MSHE), weight histogram equalization (WHE), local histogram equalization (LHE), and exposure region histogram equalization (ERHE), respectively [6].

By breaking the histogram of the original one to be two sub-histograms, the BSHE group's methodologies have been introduced to overcome the problems of the traditional HE technique. Some of these techniques are (i) dualistic sub-image histogram equalization (DSIHE) [7], (ii) brightness preserving bi-histogram equalization (BBHE) [8], (iii) otsu-based BBHE (OBBHE) [9], and (iv) entropy based BBHE (EBBHE) [9]. DSIHE maintains the brightness of the image by dividing the histogram into two parts using the median value as a division point, while BBHE uses the mean value for the division. On one hand, a high-frequency dominance is identified in the DSIHE and BBHE approaches which could add artifacts and could not reduce the noise in the resultant image [10, 3]. On the other hand, the OBBHE and EBBHE techniques use the Otsu and entropy values to divide the image's histogram. These two techniques have been proven superior the DSIHE and BBHE techniques in terms of maintaining the brightness of the image. However, the capability of these two techniques of improving the image's contrast has not been proven [11].

The techniques of the MSHE group developed with the same aim as BSHE of overcoming the limitations of HE. The MSHE techniques divide the images' histogram into multiple sub-histograms (i.e., recursively). Recursive mean-separate HE (RMSHE) [12], adaptive thresholding based sub-histogram (ATSHE) [13], entropy dynamic sub-HE (EDSHE) [14], and quadrant dynamic HE (QDHE) [15] are the techniques of the MSHE group. The Like the DSIHE technique, RMSHE uses the mean value to divide the histogram into sub-histograms but in a recursive approach. The ATSHE technique depends on the peak signal-to noise ratio (PSNR) value for determining the number of sub-histograms and then computes the standard deviation and mean values to determine the threshold values. Finally, ATSHE computes the median value as a crucial parameter to enhance the contrast of the image. The authors claimed that the ATSHE technique can preserve the brightness and improve the contrast of images. However, this technique suffers from the manual setting of the iterations, is time-consuming, and produces washed out regions and ambiguous details [3]. The EDSHE technique could address the limitations of RMSHE by computing the discrete entropy value of individual stages and comparing it with the initial value. However, the mentioned one produces a resultant image with attached artifacts and is time consuming. The QDHE technique was developed to preserve the details of images with contrast enhancement and noise reduction. The proposed technique divides the histogram to be four sub-histograms and then computes the mean value of individual sub-histogram to set the clip's value.

The techniques of the WHE group modify the histogram before enhancing the contrast of the image. Thus, the techniques set weights to gray levels and modifies and sets the intensity in the gray level according to the weight. These techniques have been proven capable of preserving the details of certain regions in the image and reducing the dominance of the high-frequency effect of the histogram. High speed quantile based HE (HSQHE) [16], weighted average multi-segment HE (WAMSHE) [17], and mean and variance based sub image HE (MVSIHE) [18] are the techniques of the WHE group. The HSQHE technique uses the parameter quantile (q) to set the number of sub-histograms of the image. Then, HSQHE normalizes and modifies all the sub-histograms. Finally, the technique equalizes the sub-histograms to present the final image. Nevertheless, setting the optimum q value is extremely subjective, requiring a highly skilled operator, and could attach artifacts to the resultant image and missing details. The WAMSHE technique also divides the image's histogram into sub-histograms and then modifies each sub-histogram before equalizing them. MVSIHE sets three threshold values to create four quantiles from the histogram on the basis of the mean and variance values. The resultant image of the MVSIHE technique does not suffer from many artifacts and preserves the brightness well. However, the MVSIHE technique could not highlight or at least preserve the details in the last quantile (i.e., the local details of the fourth region). Furthermore, MVSIHE is time consuming.

The techniques of the LHE group create small size blocks from the image to improve the tiny details to enhance the contrast of the image. These techniques attempt to address the poor uniform illumination distribution of the resultant image of the HE technique. The LHE techniques include adaptive HE (AHE) [19], contrast limited adaptive HE (CLAHE) [20], iterated adaptive entropy clip limit HE (IAECHE) [21], and dynamic clipped HE DCLHE [10]. The AHE technique produces a resultant image with homogeneous brightness [19] and an unnatural appearance [21, 22], is time consuming, and could not reduce the noise. The CLAHE technique divides the input image into small blocks along with set a value to clip the histogram to enhance the tiny details and improve the contrast of the image. This technique has been proven capable of improving the contrast of the image, but it cannot control this enhancement due to the manual intervention in managing the optimal values of the input parameters, which requires a highly skilled operator. In addition, the technique could not reduce the noise effect on the image, which could affect the natural appearance of the resultant image [6]. The authors of the IAECHE technique computed the entropy value to set the optimum value of the clip limit, which is used by the technique as the input parameter of the conventional CLAHE. The authors claimed that the IAECHE technique addresses the manual setting of the clip limit, and they divided the input image into four quarters to highlight the local details (i.e., region of interest, ROI) [21, 22]. The DCLHE technique removes all the gray levels from the histogram that do not contain intensities. Then, the minimum value of the remaining gray levels is set as the value of the clipping parameter. Finally, the HE technique is applied to equalize the histogram and produce the resultant image [10]. However, the DCLHE technique has poor capability in preserving the brightness of the image and producing a pleasant resultant image with few gray levels.

The last group derived from the HE technique is the exposure-based equalization group (ERHE). The techniques of this groups attempt to overcome the inhomogeneous brashness problem of the HE technique by dividing the histogram of the image into spans and equalizing them to produce an enhanced resultant image. Exposure based sub image HE (ESIHE) [6], adaptive bi-HE (ABHE) [23], and nonlinear exposure intensity based modification HE (NEIMHE) [24] techniques use exposure to enhance the contrast of the image. ESIHE divides the image's histogram into two subs by the use of exposure threshold. Subsequently, the mean value is used to clip the sub-histograms. Then, the HE technique is used to equalize both sub-histograms and produce the resultant enhanced image [23]. The ABHE technique considers the overexposure and underexposure regions to overcome the limitation of the ESIHE technique. The NEIMHE technique creates the five spans from the image's histogram and modified each sub-histogram before equalizing them to produce the resultant image. Nevertheless, the NEIMHE technique uses preset gray level values, which could lead to an over- or under-enhanced resultant image [22].

Several researchers reported that finding the optimum input values to enhance an image is a challenging issue and should be optimized [3, 22, 25]. Thus, researchers hybridized one of the HE derived techniques with optimization algorithms, such as particle swarm optimization (PSO) [26], the firefly algorithm [27], the whale optimization algorithm [28], and the grasshopper algorithm (GOA) [29]. The aim of using optimization algorithms is to maximize or minimize the value of the fitness function. Optimization algorithms do not require the training of a section or specific information of the problem. The authors of [3] attempted to find the maximum values of entropy and the structure similarity index (SSI) by introducing a new image quality factor named DE-SSI. The authors of [22] claimed that to obtain the optimum resultant image, the fitness function should be set as a combination of the entropy and the PSNR. For instance, the authors of [25] used the cuckoo search with OBBHE to enhance mammogram images, while the authors of [30]

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attempted to maximize the entropy value by hybridizing the PSO with gamma-correction on the basis of HE to enhance satellite images.

The concerns raised above motivate this work to suggest a new hybrid LHE approach for improving the image contrast. The proposed technique attempts to emphasize local features and increase the original image's information richness while reducing or preserving the noise amplification.

3. Proposed dynamic clip limit window size histogram equalization methodology

This research hypothesizes that having a high-quality and pleasant resultant image is dependent on the capacity of a dynamic and automated approach to emphasize information richness and features while reducing the noise in the image. Thus, the aim of the proposed dynamic clip limit window size histogram equalization (DCWHE) technique is to achieve optimum information richness (i.e., discrete entropy (DE)) and minimum noise (i.e., root mean square error (RMSE)) values between the resultant and input images. Attaining the optimal value for the DE parameter increases the information density of the image and contributes in highlighting the local features. Meanwhile, attaining the minimum RMSE will maintain the image's pleasant appearance and preserve the local details, avoiding the conventional CLAHE's over-enhancement limitation.

The proposed DCWHE technique has three stages: (A) parameters initialization, (B) parameters optimization, and (C) resultant image generation. This technique introduces the normalized clip limit (*Cnorm*), the minimum gray level (*Gmin*), the maximum gray level (*Gmax*), the swarm populations (*Populations*), the number of iterations (*Iter*), and the window size matrix (*Wsize*) in the first stage.

In the second stage, the GOA [29] is used to compute the optimum value of parameters *Cnorm* and *Wsize*. The fitness function (i.e., *DE·RMSE*) is introduced to obtain an optimum and pleasantly enhanced image by computing the optimum *Cnorm* and *Wsize* values through the iteration process of the GOA. To find the best solution, the GOA uses a meta-heuristic algorithm that replicates the social behavior of grasshoppers of different problems by using the exploration and exploitation strategy (further information of the GOA can be obtained from [29]). The computed optimum parameters (i.e., *Cnorm* and *Wsize*) are applied to the conventional CLAHE technique in the third phase to enhance the image and generate the final image. The description of all stages are presented in Sub-sections (A), (B), and (C), respectively. Fig. 1 illustrates the pseudocode of the proposed DCWHE technique.

3.1 Parameter initialization

This technique intends to address the imperfection of global enhancement, which involves performing enhancement across the entire image while neglecting the local details. Nevertheless, ignoring these "dominant" local features in the resultant image might corrupt the image structure and enhance noise (in circumstances when the image is heavily influenced by undesired noise). In the first phase, the proposed technique reads the original image and transforms it from colored scale to grayscale. From the histogram, several parameters are initialized: *Cnorm*, *Gmin*, *Gmax*, *Populations*, *Wsize*, *Populations*, and *Iter*. The initial value of the *Cnorm* parameter is set to 0. In addition, the *Gmin* and *Gmax* values are computed by assigning the lowest and greatest gray level values of the image to these parameters, respectively. The *Populations* parameter is computed from the number of peaks in the histogram of the image. The peaks of the histogram express the richness of information in the histogram of the image. For example, if the histogram of the image has 50 peaks, then the *Populations* of the GOA will be set to 50. The value of the iteration parameter is obtained by computing the length of the

```
Start
Read the original image
Convert the image from color to grayscale
Compute the histogram of the image
Initialize the parameters Cnorm =0, Gmin,
Gmax, Populations, Iter, Wsize, Clip limit
=0, OptimumWS = 0
Initialize the GOA parameters agents =
Populations, Lower bound = Gmin, Upper
bound = Gmax, maxDE =0,
minRMSE=100
For Iter <- iterations = 1
    For count (Wsize) <- OptimumWS = 4
    Compute Cnorm
    Compute DE & RMSE
    If  DE > maxDE & RMSE <
        minRMSE
        maxDE = DE, minRMSE =
        RMSE, Clip limit = Cnorm, WS =
        OptimumWS
    End If
End for
Apply Clip limit, OptimumWS to
conventional CLAHE
End
```

Figure. 1 Pseudocode of the proposed DCWHE technique

Table 1. Parameters' initialization of phase 1 of the proposed technique

Parameter title	Value
Cnorm	Clip limit of the proposed technique
Gmin	Minimum Gray level of the histogram
Gmax	Maximum gray level of the histogram
Population	Total number of peaks
Wsize	The normalized value of the histogram's peaks

histogram of the original image. For example, if the histogram of the original image starts with gray level 10 and ends with gray level 200, then the total number of gray levels will be 190; thus, the value of *Iter* will be set to 190. Finally, the value of the *Wsize* parameter is set to the normalized number of peaks. The log scaling formula is used to normalize the *Wsize* value as expressed by Eq (1).

$$Wsize = Round(\log_2 Peaks) \tag{1}$$

This parameter is applied as the input parameter along the *Cnorm* to the GOA to obtain the best fitness value in the second phase of the proposed technique. For example, if the *Wsize* value is 6, then 6 different window size values will be applied to the technique, starting from 4 (i.e., 4, 5, 6, 7, 8, and 9). Table 1 tabulates the parameters setting of the proposed DCWHE technique in the first stage.

The *Cnorm* variable will be applied in the proposed technique to achieve the optimum clip limit for producing the resultant enhanced image. While the *Gmin* and *Gmax* are used to set the search boundary (i.e., the limit to obtain the value of the *Cnorm*) of the optimization technique. This step ensure that the technique will not set a value out of the intensity of the input image, respectively. Additionally, the GOA algorithm requires number of agents to search for the optimum food source (i.e., the fitness function) which are represented in the *Population* parameter. Moreover, the proposed technique divides the input image into small contextual regions which are referred as *Wsize*. An important factor in the suggested technique is the *Wsize*, which allows the local features to be highlighted while also increasing contrast in the image.

3.2 Parameter optimization

Following the initialization of the parameters in the first phase, enhancement is performed om the image by calculating the optimum values of the *Cnorm* and *WS* parameters. The PDF of the histogram of the image is used as the input to the GOA to obtain the optimum *Cnorm*. Thus, if the histogram has 190 gray levels, then 190 PDF values will be used. This number matches the number of iterations of the GOA. In each iteration, a *Cnorm* value is selected from the PDF and applied with the *Wsize* array to compute the fitness function that is expressed by Eq. (2).

$$DE \cdot RMSE = \frac{MaxDE}{MinRMSE} \tag{2}$$

Where *MaxDE* and *MinRMSE* refer to the maximum details (i.e., information richness) and the minimum root noise of the image, respectively. The combination of *DE* and *RMSE* as the parameters for computing the fitness function represents the capability to present the information richness and the to present the impact of noise and artifacts in the final image. Accordingly, a high *DE* value indicates rich information, while a low *RMSE* value indicates reduced noise and artifacts in the final image. In each iteration, the value of the fitness function (i.e., *DE·RMSE*) is compared with the previous computed value. If the condition of the fitness function becomes true (i.e., *DE* if larger than *maxDE*, and *RMSE* is smaller than *minRMSE*), then the value of *maxDE* is set to that of *DE*, and that of *minRMSE* is set to that of *RMSE*. In addition, the corresponding *Clip limit* and *WS* are set as the *Cnorm* and the *OptimumWS*, respectively. In each iteration, few rounds of *WS* are applied to obtain the best *WS* for the computed *Cnorm*. Table 3 presents an example of selecting the optimum *Cnorm* with *OptimumWS* values. The aim of using the GOA is to make the technique adaptive and automatic in terms of setting the input parameters to enhance the contrast of the image. Thus, this technique is intelligent and does not depend on human experience. The GOA spreads its agents to search for the optimum food source (i.e., *DE·RMSE*) by computing the optimum *Cnorm* and *Wsize* values. Then, the selected *Cnorm* and *Wsize* values are applied to the conventional CLAHE to enhance the image and produce an optimum and pleasant resultant image. The high *DE* value proves the capability of the technique to enhance tiny details and improve the image's contrast, while the low *RMSE* value proves the capability of the technique to enhance the image without or with minimum noise amplifications. Table 2 and 3 list the possible combinations of the *DE* and *RMSE* parameters to produce the optimum fitness function, and an example of the *Cnorm* with *Wsize* selection in four iterations, respectively.

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Table 2. The possible combination of DE and RMSE values

DE	RMSE	MaxDE & MinRMSE
Low	Low	Not match
High	Low	Match
Low	High	Not match
High	High	Not match

Table 3. Selecting the optimum *Cnorm* with *OptimumWS* values

Iteration	Cnorm	Wsize
1	0.028	3
		4
		5
2	0.329	3
		4
		5
3	0.100	3
		4
		5
4	0.063	3
		4
		5

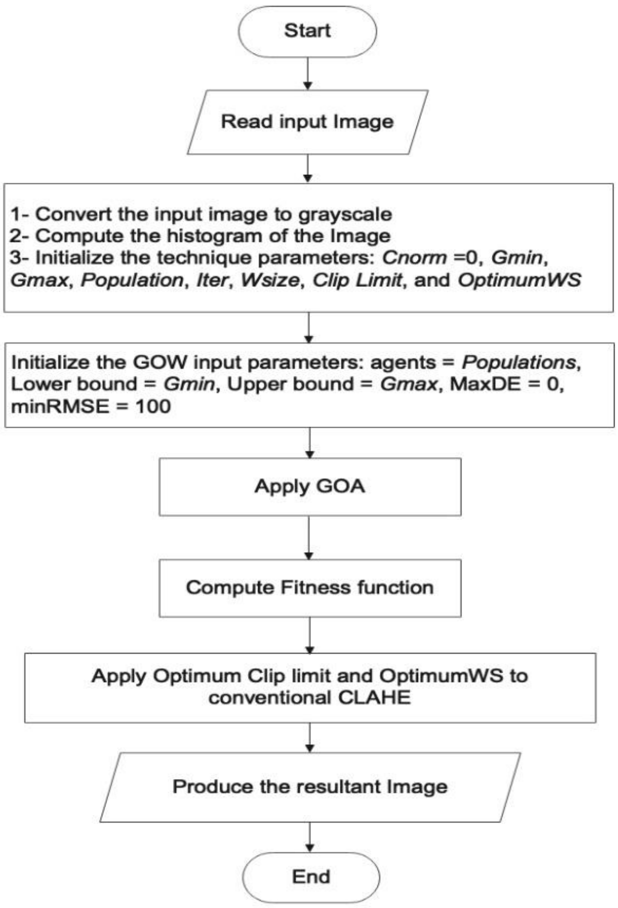

Figure. 2 The flowchart of the proposed DCWHE technique

3.3 Resultant image generation

After selecting the optimum *Cnorm* and *WS* values, these two parameters are applied to the conventional CLAHE to produce the resultant image. Using the optimum *Cnorm* and *WS* values could affect the contrast enhancement while highlighting the local details and reducing the noise and artifacts of the image. Fig. 2 Illustrates the flowchart of the proposed DCWHE technique.

3.4 Contribution of the DCWHE technique

- The DCWHE technique provides local enhancement for the image to overcome the under- and over-contrast problems by automatically and adaptively setting an optimum clip limit and window size values.
- DCWHE highlights the local details of the image, preserving the minimum noise and artifacts amplification and achieving optimum contrast enhancement by introducing a new fitness function, namely, *DE·RMSE*. This new fitness function is submitted to overcome the conventional CLAHE limitations.
- The values of the parameters are determined automatically and adaptively by DCWHE. Meanwhile, the CLAHE calculates those certain values manually through observation and experimentation, which is time-consuming for the user and depending on their abilities and expertise. In certain circumstances, this subjective procedure could provide poor values, resulting in poor enhancements results.

According to the above criteria, DCWHE can produce a pleasant resultant image compared with the state-of-the-art enhancement techniques, specifically the techniques derived from HE.

4. Datasets and evaluation metrics

To evaluate the performance of DCWHE, a test was performed on 691 sample images. Of the images examined, 241 were from the Pasadena-houses-2000 dataset [31], and 450 were from the Faces-1999 dataset [32]. These images were obtained from the databases of Image Processing Place, California Institute of Technology and Standard Diabetic Retinopathy and selected for the ROI distribution of the information contained in these images. This research primarily focused on grayscale images for analysis purposes, and the examined approaches were implemented in the spatial domain and based of conventional HE.

The performance of the proposed DCWHE technique was compared with five state-of-the-art techniques, namely, CLAHE [20], AEIHE [3], ACLTSHE [22], HSQHE [16], and IAECHE [21]. These techniques were selected based on the following: (i) based on the HE technique, (ii) adaptive and automatic parameters, (iii) in the spatial domain, (iv) recently published (i.e., within the last 5 years), and (v) highlight the local details. The evaluation process performed by qualitative and quantitative approaches verifies the capability of the proposed DCWHE technique. For the qualitative assessment, a sample image was collected and subjected to all techniques, and the results of each technique are presented to highlight its strengths and limitations. Quantitative analyses were performed by computing five quantitative parameters for the sample images of Pasadena-houses 2000, Faces-1999, and average values for the datasets to the proposed technique along with the compared techniques. The selected metrics are as follows: the contrast improvement index (CII), the SSI, the RMSE, DE, and the average mean brightness error (AMBE). The CII parameter was selected because it evaluates the contrast improvement between the original and final images [33]. The SSI presents the similarity between the resultant and input images, and the structure is not distorted [34]. The RMSE parameter refers to the noise and artifacts of the image; thus, a small value indicate minimal noise and artifacts in the image, while a large value indicates distortion in the image and that the ROIs contain much noise [22]. The AMBE parameter is used to present the capability of the technique to sustain the image's brightness [22]. The DE parameter refers to the information richness of the image [35].

5. Results and discussion

Qualitative and quantitative assessments were applied to assess the performance of the DCWHE technique. The performance of the proposed DCWHE technique is compared that of five state-of-the-art techniques, namely, CLAHE [20], AEIHE [3], ACLTSHE [22], HSQHE [16], and IAECHE [21]. According to the authors of the techniques for comparison, optimal parameters values are adopted in their compared techniques. The results of the qualitative assessment are illustrated by using sample images from the Pasadena-houses-2000 and Faces-1999 datasets. The sample image from the Faces-1999 dataset is presented in Figure 3. Figure 4 presents the magnified region of the sample image. Figures 5 and 6 show the sample image from the Pasadena houses-2000 dataset and its magnified region, respectively. The qualitative analyses are supported by the quantitative analyses results in Tables 4 and 5. The best value is in bold format, while the second-best value is underlined. Table 6 provides the average values of all the quantitative parameters.

The qualitative assessment of the sample image from the Faces-1999 dataset is shown in Figure 3. The HSQHE technique barely enhanced the sample image, as shown in Fig. 3(b). Additionally, the resultant image of the HSQHE technique suffers from artifacts in the ROI (i.e., the spots in the face region). The magnified area of the image shows artifacts in the face region Fig. 4(b)). The resultant images of the ACLTSHE, CLAHE, and IAECHE techniques suffer from over contrast, which is obvious in Fig. 3(c), (d), and (f), respectively. This over contrast distorted the natural appearance of the image and amplified the noise in the image. The magnified area of the resultant images proves that these techniques have poor capability of maintaining the natural appearance of the image and controlling the contrast enhancement, as shown in Fig. 4(c), (d), and (f). The resultant image of AEIHE is pleasant and clearer than those of the other techniques. The splitting issue of this technique is obvious and clear in the right part of the image, and the border line between the center and right sub-images is clear and obvious in the resultant image, as shown in Fig. 3(e). The final image of the DCWHE technique proves its high capability of improving the contrast of the image while preserving the noise from amplification. Unlike AEIHE, the final image of the proposed technique does not suffer from the border line issue. The proposed technique can produce a clear and pleasant resultant image compared with other state-of-the art techniques. Additionally, the proposed technique can highlight the local details pleasantly better than the other techniques as illustrated by the beard of the human in the image in the magnified area of Fig. 4(g). These findings are supported by the values in Table 4. Although the IAECHE technique could produce the best AMBE value, the visual appearance of the resultant image in Fig. 3(f) shows the inhomogeneous brightness of the enhanced image, which affects the quality of the image. In contrast, the proposed DWCHE technique can produce the second-best DE, and RMSE values (i.e., 7.869, and 5.038, respectively) as shown in Table 4. These values prove the DWCHE technique's high capability of increasing the information richness, maintaining the noise from amplification, and preserving the brightness of the image while producing a resultant image with balanced contrast. Furthermore, most the compared techniques, including the proposed technique, were able to preserve the input image's

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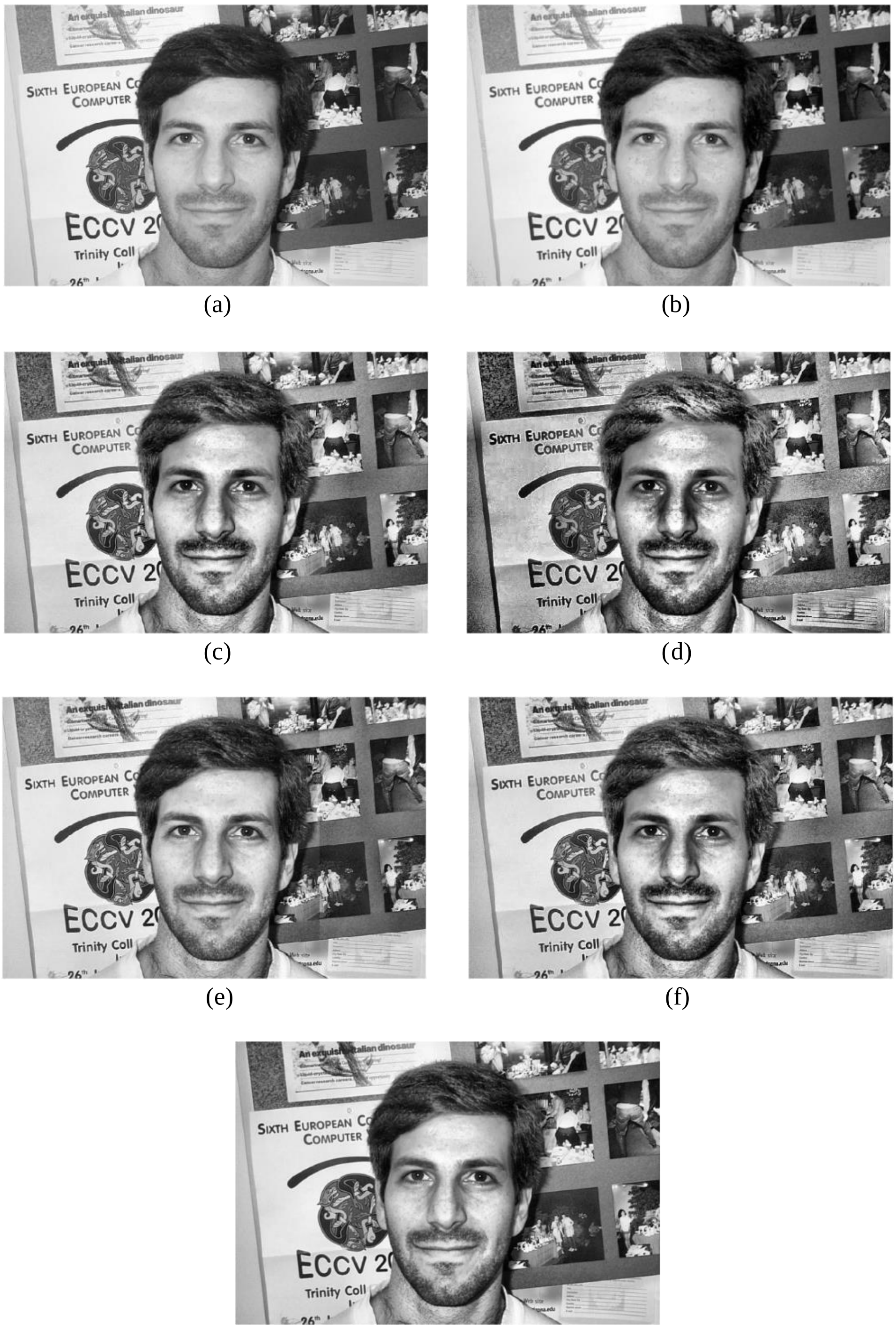

(a) (b) (c) (d) (e) (f) (g)

Figure. 3: (a) Sample image of Faces-1999, (b) HSQHE, (c) ACLTSHE, (d) CLAHE, (e) AEIHE, (f) IAECHE, and (g) proposed technique

structure. Thus, this high ability to preserve the structure is supported by the contrast improvement value in Table 4.

The HSQHE technique does improve the contrast of the sample image from the Pasadena-houses-2000 dataset greatly, as shown in Fig. 5(b), and the magnified area is blurred, indicating the loss of local details and the impact on the (ROI)s of the image, as shown in Fig. 6(b). The final images of the ACLTSHE, CLAHE, and IAECHE techniques suffer from over contrast. This problem affects the visual appearance of the image and the homogeneous regions, such as the sky distortion behind the house, as shown in Fig. 5(c), (d), and (f). Additionally, the magnified areas of these resultant images suffer from

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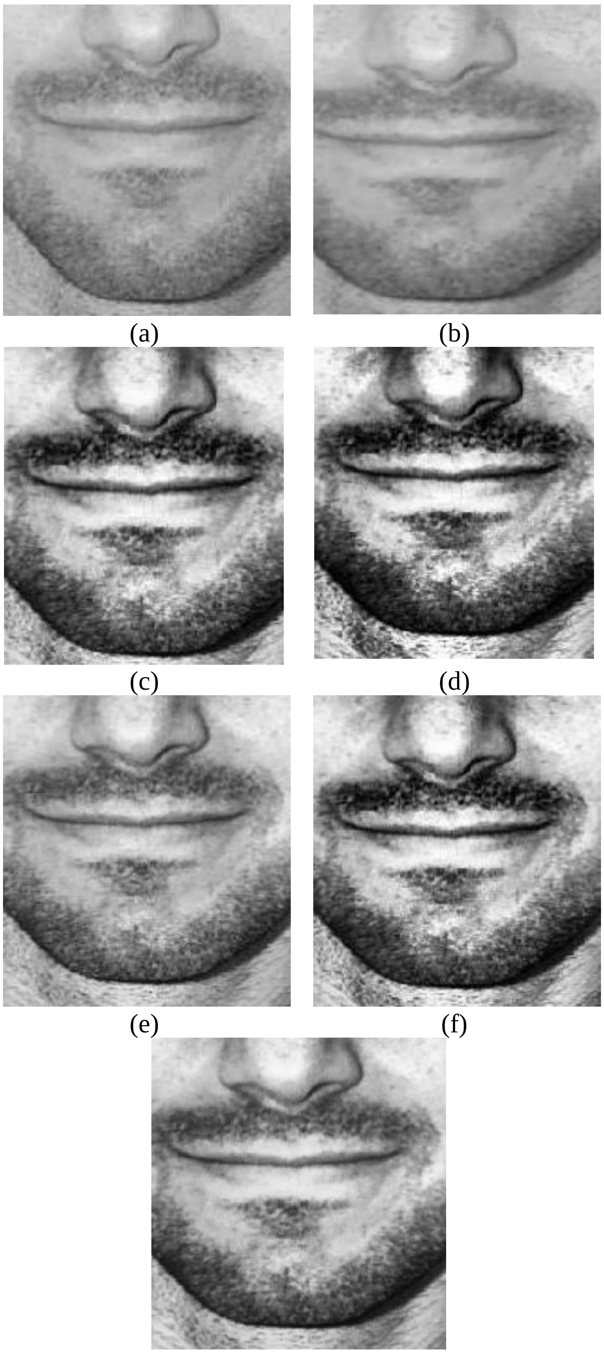

(g)
Figure. 4: (a) Magnified area, (b) HSQHE, (c) ACLTSHE, (d) CLAHE, (e) AEIHE, (f) IAECHE, and (g) proposed technique

noise amplification and high signal, which can be observed on the statue inside the magnified area in Fig. 6(c) and (d). The resultant images of AEIHE and the proposed technique were enhanced better than the those of the other techniques. These two techniques were able to produce pleasant images with minimum noise amplification, as shown in Fig. 5(e) and (g). Additionally, the proposed technique could improve the brightness of the image over the fair distribution of the brightness into the image, exhibiting a superior capability of improving the visual appearance of the image as shown by the doorsteps in the magnified area of Fig. 6(g). These findings are supported by the values in Table 5. The proposed DCWHE technique could produce the second-best RMSE and SSI, and the best CII values of the sample image from the Faces-1999 dataset. These values indicate the DCWHE technique's high capability of maintaining the noise from amplification during image enhancement.

The assessment of the proposed and comparison techniques was performed by computing the average value of the quality factors (i.e., AMBE, DE, RMSE, CII, and SSI) for the images from the datasets. The proposed technique's high capability of improving the information richness and highlighting the local details of the image while maintaining minimum noise amplification for sample image from the Pasadena-houses 2000 dataset are proven. The proposed (DCWHE) technique produced the best average DE value on the Pasadena-houses 2000 dataset (i.e., 7.926), while the AEIHE technique produced the second-best DE value (i.e., 7.778) as tabulated in Table 6. Additionally, the proposed DCWHE technique produced the second-best average RMSE value om the Pasadena-houses 2000 dataset (i.e., 7.508) with a small fraction of difference from the best average value of the AEIHE technique (i.e., 6.910). This small difference proves the high capability of the proposed DWCHE technique of highlighting the local details without or with minimum noise amplification. According to the average assessment values for the Faces-1999 dataset, the proposed DCWHE technique produced markable values by producing a high average DE and a low average RMSE. In addition, the proposed DWCHE and the comparison techniques proved their high capability of preserving the structure (i.e., SSI) while enhancing the contrast (i.e., CII) of the image as tabulated in Table 6.

The assessment of the proposed and the compare techniques also done by computing the average value of the quality factors (i.e., AMBE, DE, RMSE, CII, and SSI) for the images of the datasets. The proposed technique proved its high capability of improving the information richness and highlight the local details of the image along of maintaining the minimum noise amplification for the Pasadena-houses 2000 dataset. The proposed (DCWHE) technique was able to produce the best average DE value of the Pasadena houses-2000 (i.e., 7.926), while the AEIHE technique produced the second-best DE values (i.e., 7.778) as tabulated in Table.6. Additionally, the proposed DCWHE technique was able to produce the second-

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(a)

(b)

(c)

(d)

(e)

(f)

(g)

Figure. 5: (a) Sample image of Pasadena houses-2000, (b) HSQHE, (c) ACLTSHE, (d) CLAHE, (e) AEIHE, (f) IAECHE, and (g) proposed technique

best average RMSE value to the Pasadena houses-2000 dataset (i.e., 7.508) with small fraction of difference compared with the best average value of the AEIHE technique (i.e., 6.910). This small difference proves the high capability of the proposed DCWHE technique to highlight the local details without or with minimum noise amplification of the image.

As the average assessment values of the faces-1999 dataset, the proposed DCWHE technique was able to produce a markable values by producing a high value of average DE and low value of the average RMSE parameters. In addition, the proposed DCWHE and the compared techniques proved their high capability of preserving the structure (i.e., SSI)

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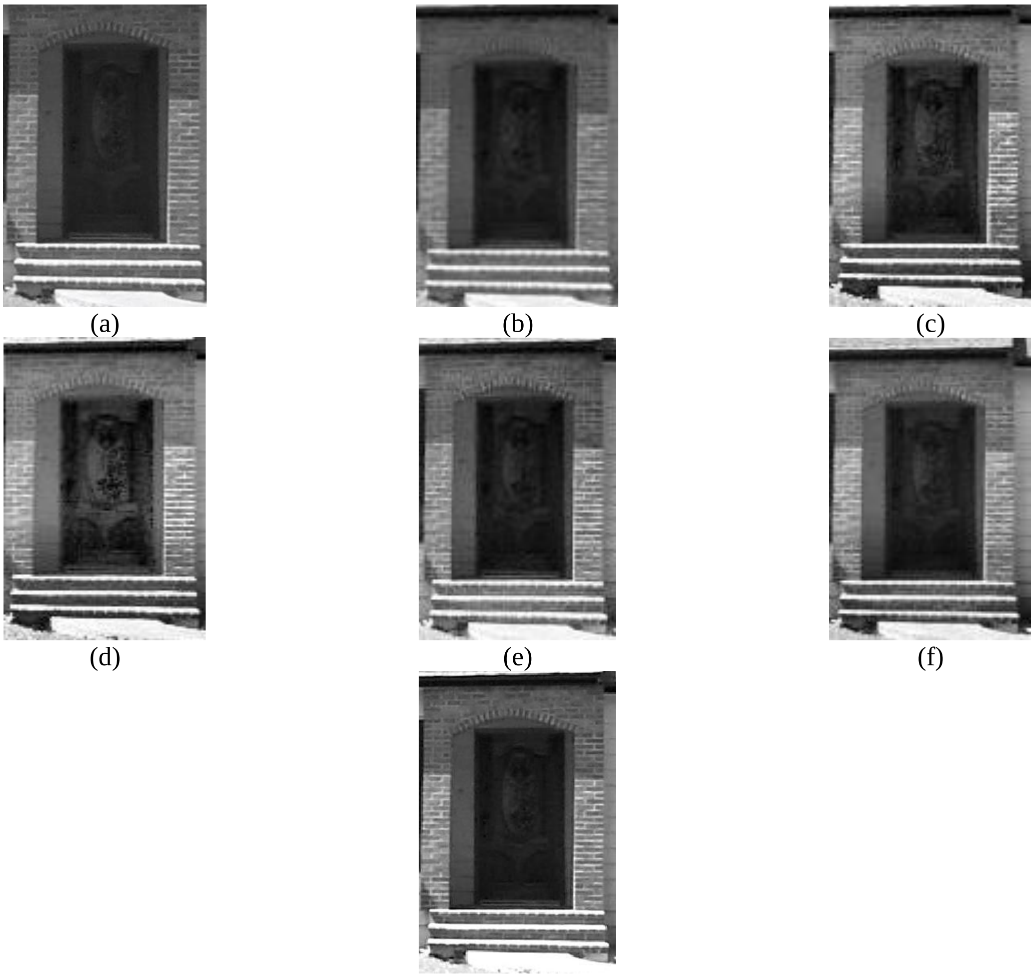

Figure. 6: (a) Magnified area, (b) HSQHE, (c) ACLTSHE, (d) CLAHE, (e) AEIHE, (f) IAECHE, and (g) proposed technique

Table 4. Analytical findings from the Faces-1999 sample image

Technique	AMBE	DE	RMSE	CII	SSI
HSQHE [16]	0.999	7.754	**2.000**	**1.000**	**0.999**
CLAHE [20]	2.941	7.962	9.253	0.983	0.593
ACLTSHE [22]	0.774	7.819	8.968	0.997	0.932
AEIHE [3]	0.629	7.776	8.140	0.996	0.892
IAECHE [21]	**0.560**	7.770	8.203	0.995	0.941
Proposed DCWHE	0.701	**7.869**	5.038	**1.000**	**0.999**

Table 5. Analytical findings from the Pasadena-houses-2000 sample image

Technique	AMBE	DE	RMSE	CII	SSI
HSQHE [16]	**1.396**	7.780	**3.479**	1.000	**0.999**
CLAHE [20]	5.851	**7.940**	9.443	0.981	0.720
ACLTSHE [22]	4.273	7.867	8.496	1.010	0.920
AEIHE [3]	5.219	7.823	8.979	0.984	0.899
IAECHE [21]	4.896	7.802	8.778	1.000	0.939
Proposed DCWHE	5.964	7.832	5.944	**1.017**	0.964

Table 6. Faces-1999 and Pasadena houses-2000 datasets average quantitative values

Dataset	Technique	AMBE	DE	RMSE	CII	SSI
Pasadena-houses-2000	HSQHE [16]	**3.372**	7.574	8.205	**1.027**	0.899
	CLAHE [20]	6.605	7.285	9.072	1.014	0.716
	ACLTSHE [22]	9.078	7.658	9.750	1.021	0.882
	AEIHE [3]	6.358	7.778	**6.910**	0.990	0.877
	IAECHE [21]	7.000	7.345	7.715	0.980	**0.900**
	Proposed DCWHE	6.945	**7.926**	7.508	0.985	0.880
Faces- 1999	HSQHE [16]	**1.481**	7.624	4.210	1.002	0.897
	CLAHE [20]	21.696	7.928	4.234	**1.042**	0.473
	ACLTSHE [22]	9.025	7.686	**3.363**	1.026	0.900
	AEIHE [3]	6.207	7.935	4.853	0.982	**0.903**
	IAECHE [21]	9.125	**8.000**	3.961	0.898	0.901
	Proposed DCWHE	7.102	7.607	9.571	0.980	0.870

while enhancing the contrast (i.e., CII) of the image as tabulated in Table.6.

To summarize, the proposed approach demonstrated its excellent ability by generating pleasant resultant image with minimum noise amplification, highlighting the local details a long of high quantitive values of the sample photos as well as high average quantitive values of the image quality elements of the datasets studied (i.e., 691 images). In addition, the DCWHE technique produced the best DE, CII, and SSI values for the faces 1999 sample image (7.869, 1000, and 0.999, respectively). While results of the pasadena-houses-2000 sample images were second-best RMSE, best CII, and second-best SII values (5.944, 1.017, and 0.964, respectively).

The average results of the suggested technique produced the best DE value of the Pasadena-houses-2000 dataset (7.926) and the second-best value of the RMSE (7.508) as compared with the state-of-the-art techniques. Moreover, the suggested technique was able to produce a markable average results for the Faces-1999 dataset images and proves its high capability to highlight the local details and improve the contrast of the image.

6. Conclusion

This research presents DCWHE, a novel adaptive and automatic variant of the conventional CLAHE technique, to address the subjective impacts of the manual parameter setting by automatically and adaptively estimating the optimum clip limit and the window size. To obtain the optimal entropy with minimum noise amplification, a novel fitness function called *DE·RMSE* is presented. The proposed technique was validated on the Pasadena-houses 2000 and Faces-1999 datasets. According to the qualitative and quantitative results, the DCWHE technique competitive performance on the two distinct datasets. DCWHE's high DE value proves its capacity to improve the image and generate an optimum and pleasant resultant image. The DCWHE technique effectively increases the image's information richness and highlights the local details with minimal unwanted distortion and noise amplification in the resulting images. The high DE value and the maintained noise from amplification indicate the high ability of the proposed DCWHE technique to produce a pleasant final image.

In summary the DCWHE technique proved its high capability by producing high quantitive values of the sample images, and high average quantitive values of the image quality factors of the tested datasets (i.e., 691 images). The proposed technique was able to produce the best DE, CII, and SSI values of the faces 1999 sample image (7.869, 1000, and 0.999, respectively). The second-best RMSE, best CII, and second-best SII values of the pasadena-houses-2000 sample image (5.944, 1.017, and 0.964, respectively). Additionally, the proposed technique proved its high capability of producing the best DE value of the Pasadena-houses-2000 dataset (7.926) and the second-best value of the RMSE (7.508) as compared with the values to the state-of-the-art techniques.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper background work, conceptualization, methodology and result analysis and comparison have been done by first and second authors. Dataset collection, implementation, preparing and editing draft, visualization have been done by third and fourth authors. The review of work and project administration have been done by fourth author.

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