Low Light Image Contrast Enhancement Based on Linear Fusion with an Optimized Weight

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***Abstract*—This paper presents an approach to low light image contrast enhancement whose objective is to improve the visual quality of an image. To this end, we apply a linear image fusion with two images in this study. The two images are the input image and its histogram equalized image. For better performance, we use a metaheuristic optimization algorithm called the whale optimization algorithm to find an optimal weight for the linear fusion, where a patch-based contrast quality index is used as a fitness function. The proposed approach is verified by two hundred low light images. The result indicates that our approach performs better than the comparison approaches, that is, conventional histogram and contrast limited adaptive histogram equalization, in terms of patch-based contrast quality index and subjective visual quality.**

Keywords—contrast enhancement, histogram equalization, linear image fusion, whale optimization algorithm, patch-based contrast quality index

I. Introduction

In the image processing community, contrast enhancement has been an active field because it improves image quality for human vision or performance for the following applications, such as medical imaging, remote sensing, surveillance, and photography. Image contrast enhancement generally refers to improving the visual quality of an image by adjusting its brightness and contrast levels. In other words, it involves various techniques to improve the visual quality and detail perception of images by increasing the distinction between light and dark areas. Three methods are commonly found on this topic. The first is the histogram equalization, for example [1-3], which redistributes the pixel intensities for a more uniform histogram. The second is the gamma correction which adjusts the gamma value to alter the relationship between intensity values and displayed brightness, e.g., [4-5]. The third is image fusion, which combines information from multiple images into a final image to improve contrast with improved contrast and dynamic range, for example, [6-7].

As a subfield of image contrast enhancement, low light image contrast enhancement is a more challenging task, since the darkness in an image covers details such that they are invisible. To eliminate the problem, this paper proposes a novel framework for low light image contrast enhancement that combines histogram equalization and linear image fusion. Our approach consists of three stages. First, a histogram equalized image is obtained from the input image to extract complementary details. Second, a linear fusion, with a weight, to combine the input image and its histogram equalized image. Third, an optimal weight is found for the linear fusion using a metaheuristic optimization algorithm, that is, the whale optimization algorithm (WOA) [8], with a fitness function, PCQI [9].

This paper is organized as follows. Section II provides a brief review of histogram equalization, WOA, and PCQI. Section III describes the motivation for this study and then introduces the proposed approach. Section IV justifies our approach with examples. Finally, Section V concludes this paper.

II. Review

The section gives a brief review of histogram equalization, WOA, and PCQI, which are used in the proposed approach.

A. Conventional Histogram Equalization

A conventional histogram equalization (CHE) is a scheme to enhance the contrast in an image by pixel probability density and its cumulative distribution. Assume an L-level input image $\boldsymbol{I}_i$ whose pixel value of k is denoted as x_k. Then the probability density $p(x_k)$ of x_k is calculated as below.

$$p(x_k) = \frac{n_k}{N} \text{ for } k = 0, \cdots, L-1 \qquad (1)$$

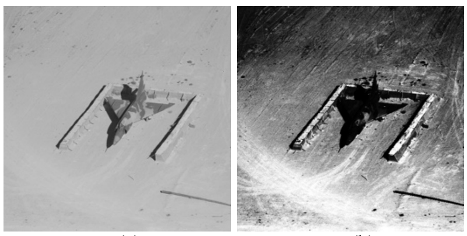
where n_k is the total number pixels whose value is x_k and N is the total number of pixels in $\boldsymbol{I}_i$. Next, the cumulative distribution of $p(x_k)$ is calculated as below.

$$c(x_k) = \sum_{i=0}^{k} p(x_k) \qquad (2)$$

By $c(x_k)$, the pixel value $x_{k'}$ in the equalized image $\boldsymbol{I}_h$ of $\boldsymbol{I}_i$ is found as below.

$$x_{k'} = L \times c(x_k) \qquad (3)$$

The image 'Airplane' is used as an example to show the effect of CHE. The original image is shown in Fig. 1(a) and its equalized image after the CHE is shown in Fig. 1(b). In the example, the contrast in the original 'Airplane' was enhanced by the CHE. However, it has an over-enhancement problem, that is, it loses details of the airplane object, although the detail of road area was enhancement. It is also observed that in the input image the not obvious details have been enhanced in the CHE equalized image, for example, the road area. On the other hand, the lost details in the enhanced image can be found in the input image, e.g., the aircraft object. The complementary property will be used in the proposed linear image fusion.



(a) (b)

Fig. 1. An example for the CHE (a) original image (b) after the CHE

B. The Whale Opitmization Algorithm

The whale optimization algorithm (WOA) is a metaheuristic optimization algorithm proposed in [8]. It is

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inspired by the social behavior and bubble-net hunting of humpback whales in oceans. The algorithm simulates the foraging behavior of humpback whales, including exploration, encircling prey, and bubble-net feeding behavior to find optimal solutions. In the exploration phase, the search agent (humpback whale) looks for the best solution (prey) randomly based on the position of each agent. The position of a search agent is updated during this phase using a randomly selected search agent rather than the best search agent. In the encircling phase, humpback whales encircle the prey during hunting. They considered the current best candidate solution as the best solution and near the optimal one. In the exploitation phase, humpback whales attack prey using a bubble-net method. The WOA is composed of three stages: encircling the prey, spiral bubble-net feeding maneuver, and prey searching. The pseudocode of WOA is given in Table I. For more details, see [8].

TABLE I. THE PSEUDO CODE FOR WOA IN [8]

Initialize the whale population $\vec{X}_i$ of N_w and
  the maximum number of iterations $t_{\max}$
Calculate the fitness of each search agent $\vec{X}_i$
Find the initial best search agent $\vec{X}^*$
while ($t < t_{\max}$)
  for each search agent $\vec{X}_i$
   Update $\vec{a}$, $\vec{A}$, $\vec{C}$, l and p
 if ($p < 0.5$)
   if ($|\vec{A}| < 1$)
    Update $\vec{X}_i$
  else if ($|\vec{A}| \geq 1$)
   Randomly select $\vec{X}_{rand}$ from the population
   Update $\vec{X}_i$ by
  endif
 elseif ($p \geq 0.5$)
   Update $\vec{X}_i$
 end if
  end for
  Adjust all $\vec{X}_i$ if they are out of solution range
  Calculate the fitness of all $\vec{X}_i$
  Update $\vec{X}^*$ if a better $\vec{X}_i$ is found
  $t = t + 1$
end while
return $\vec{X}^*$

In this study, with PCQI as the fitness function, the resulting optimal solution $\vec{X}^*$ in the WOA will be the optimal weight w^* for the proposed linear image fusion.

C. Patch-Based Contrast Quality Index

In [9], Wang at el. presented a method to assess the quality of contrast-changed images by decomposing image patches and evaluating their perceptual distortions. The method decomposes image patches into mean intensity, signal strength, and signal structure components and evaluates their perceptual distortions. Accordingly, a patch-based contrast quality index (PCQI) was developed which produces a local contrast quality map to predict local quality variations over space. For details, see [9]. Assume $\boldsymbol{x}$ and $\boldsymbol{y}$ are a pair of co-located patches in the original image $\boldsymbol{X}$ and the test image $\boldsymbol{Y}$, respectively. A local PCQI for $\boldsymbol{x}$ and $\boldsymbol{y}$ is found in the following.

$$PCQI(\boldsymbol{x},\boldsymbol{y}) = q_i(\boldsymbol{x},\boldsymbol{y}) \cdot q_c(\boldsymbol{x},\boldsymbol{y}) \cdot q_s(\boldsymbol{x},\boldsymbol{y}) \quad (4)$$

where $q_i(\boldsymbol{x},\boldsymbol{y})$, $q_c(\boldsymbol{x},\boldsymbol{y})$, and $q_s(\boldsymbol{x},\boldsymbol{y})$ relates to the mean intensity difference, the contrast change, and structure distortion, respectively. The overall PCQI for images $\boldsymbol{X}$ and $\boldsymbol{Y}$ is calculated as follows.

$$PCQI(\boldsymbol{X},\boldsymbol{Y}) = \frac{1}{M}\sum_{i=1}^{M} PCQI(\boldsymbol{x}_i,\boldsymbol{y}_i) \quad (5)$$

where M is the number of patches in $\boldsymbol{X}$. It should be mentioned that $PCQI(\boldsymbol{X},\boldsymbol{Y}) = 1$ when $\boldsymbol{X} = \boldsymbol{Y}$. When $PCQI(\boldsymbol{X},\boldsymbol{Y})$ is greater than 1, it means that image $\boldsymbol{Y}$ has a better contrast quality than that in $\boldsymbol{X}$ and vice versa. It has been reported to have excellent performance to evaluate contrast enhancement performance. Thus, it is used in the WOA to find an optimal solution for the proposed linear image fusion, where a fused image by the proposed linear fusion is used as the test image $\boldsymbol{Y}$.

III. THE PROPOSED APPROACH

In this paper, we use a linear fusion to improve the contrast in an image where two images with complementary details are desired for better performance. By the result in Fig. 1, we observe that the detail in the input image and its CHE equalized image has this property. Thus, they are used in our approach. Note that the proposed approach requires only one image, i.e., the input image, since the other image is derived from the input image. Consequently, the proposed approach can be easily used in the real- world applications. In our approach, the linear image fusion (LIF) is expressed as follows.

$$\boldsymbol{I}_f = w\boldsymbol{I}_i + (1-w)\boldsymbol{I}_h \quad (6)$$

where $\boldsymbol{I}_i$ is the input image; $\boldsymbol{I}_h$ is the equalized image of $\boldsymbol{I}_i$; $\boldsymbol{I}_f$ is the fused image; and $w \in (0, 1)$ is a weighting factor.

In order to find an optimal weight w in Eq. (6), the WOA is applied in this study, where the PCQI is used as the fitness function. Given an input image $\boldsymbol{I}$, the steps to implement the proposed approach are given below.

Step 1. Perform the CHE to obtain the equalized image $\boldsymbol{I}_h$.

Step 2. Use the LIF in Eq. (6) to find the fused image $\boldsymbol{I}_f$.

Step 3. Search an optimal weight w^* using the WOA for the LIF.

Step 4. Obtain the final enhanced image by the LIF with w^*.

The overall block diagram of our approach is depicted in Fig. 2 where t is the current number of iterations. In the following experiment, the parameters in the WOA were set as $N_w = 10$ and $t_{\max} = 10$.

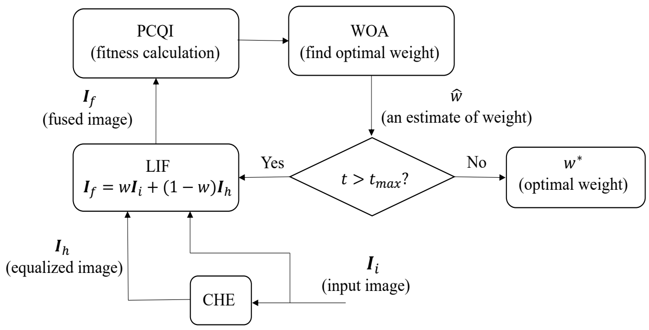

Fig. 2. The block diagram of our approach

IV. RESULTS AND DISCUSSION

In this section, the proposed approach is verified using the dark face (DF) data set [10], which is a collection of 6,000 low light images. In the experiment, 200 images were randomly selected from the DF data set. The selected examples were used to verify the proposed approach. Furthermore, our approach was compared to CHE and CLAHE [11]. In the following experiment, it included three parts: determination of color space, PCQI comparison, and subjective comparison.

A. Determination of Color Space

To investigate how the color space affects the performance of our approach, in the first experiment, we evaluated our approach with different color spaces, that is, RGB and LAB, in terms of PCQI. The result is shown in Table II, which indicates that the RGB color space is a better choice for the given DF examples. Consequently, RGB color space was used in the following experiment.

TABLE II. THE RESULT OF OUR APPROACH USING RGB AND LAB

	RGB	LAB
PCQI	1.103	1.044

B. PCQI comparison

Here, the PCQI comparison was made for our approach, CLAHE and CHE, whose results are given in Table III. The result shows that our approach has the best PCQI, while the second is for the CLAHE, and the third is for the CHE. As described previously, the PCQI greater than 1 suggests that the contrast in the input image has been enhanced and better visual quality is expected. Thus, the PCQI result in Table III implies that the best visual quality is for the proposed approach, then for the CLAHE and CHE. This is justified in the following.

TABLE III. THE PCQI COMPARISON OF OUR APPROACH, CLAHE, AND CHE

	Our approach	CLAHE	CHE
PCQI	1.103	1.091	0.937

C. Subjective comparison

For subjective comparison, eight images of the contrast enhanced images were selected, which were obtained by the proposed approach, CLAHE, and CHE. They are shown in Table IV, where the corresponding PCQI is given as a reference. In Table IV, the result shows that the CHE generally has an over enhancement problem, which loses details in some area, even its brightness being significantly improved. Moreover, the CHE has severe color distortion in all cases. As for the CLAHE, it does not have a problem like the CHE and outperforms the proposed approach in two examples with a bald red ink in the PCQI value. In addition, enhanced images by the CLAHE generally have the problem of detail loss in dark areas. On the contrary, the visual quality of the enhanced image by our approach is generally superior to that of CLAHE in restoring details and maintaining the tone of the input image. The result is consistent with the PCQI. In summary, the proposed approach outperforms the CHE and is generally better than the CLAHE in the given examples.

V. CONCLUSION

This paper has presented an approach to low light image contrast enhancement by using linear fusion with optimal weight. The optimal weight was obtained by the WOA with PCQI as the fitness function. The proposed approach was verified by two hundred images selected from the dark face data set. Furthermore, our approach was compared to CLAHE and CHE. The result indicates that the proposed approach performs better than the comparison approaches in both PCQI and subjective visual quality. Furthermore, our approach requires only one image. It implies that our approach can be easily used in the real-world applications to improve the contrast in a low light image.

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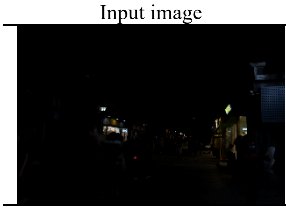
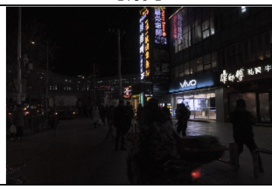
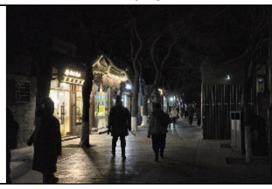
TABLE IV. SUBJECTIVE COMPARISON OF OUR APPROACH, CLAHE, AND CHE

Input image	Our approach	CLAHE	CHE
			
PCQI	1.157	1.091	0.993
			
PCQI	1.112	1.058	0.935
			
PCQI	1.128	**1.145**	1.004
			
PCQI	1.249	1.182	1.095
			
PCQI	1.107	1.074	0.927
			
PCQI	1.062	**1.193**	0.982
			
PCQI	1.121	1.048	0.949
			
PCQI	1.195	1.144	1.009