An effective approach for low-light image enhancement

Phu-Hung Dinh[1]

Abstract: Low-light image enhancement plays an essential role in many applications of image processing. According to our observations, although many methods have been proposed to solve this problem, the obtained enhanced image may be lost in detail. This paper presents a new approach to solve the above problem. First, we introduce a method of decomposing an image into two components based on a Gaussian filter. Then, this image decomposition method is applied to decompose the input image into two components, the base layer (I_{BL}) and detail layer (I_{DL}). Local Brightening (LB) method is applied to the I_{BL} component, obtaining the I_{LB} component. The Laplacian edge detection (LED) operator is applied to the detail component (I_{DL}), yielding the feature component (I_{LED}). The Marine predators algorithm (MPA) is applied to find the suitable parameters (β_1, β_2, and β_3) for the I_{LB}, I_{DL}, and I_{LED} components. Finally, the enhanced image is calculated as the sum of the components (I_{LB}, I_{DL}, and I_{LED}) multiplied by the corresponding adaptation coefficients. Four evaluation indexes, three image enhancement algorithms, three other optimization algorithms, and 95 low-light images were used and evaluated. The experimental results show that the proposed method effectively enhances image quality and ensures sharp images.

Keywords: Low-light image enhancement, Gaussian filter, MPA.

1. Introduction

Low-light image enhancement has many practical applications, such as image segmentation, target detection (Wang & Zhong, 2021), and tracking (Chu et al., 2017). Therefore, it is necessary to develop algorithms to improve image enhancement performance in low light conditions. The traditional approaches to solving this problem are those based on histogram equalization. For example, Histogram equalization (HE) (Cheng & Shi, 2004) improves light intensity by expanding the image's dynamic range so that details hidden in dark areas are re-displayed. Some other methods can be mentioned: adaptive histogram equalization (AHE) and Contrast Limited Adaptive Histogram Equalization (CLAHE). However, these methods rarely consider lighting factors in practice, which can lead to the unnaturalness of the final output.

Other approaches are based on the Retinex theory. It is assumed that the human-observed image can be decomposed into two components called reflection and illumination. For example, Fu et al. (2016) introduced a weighted variational method to estimate reflectance as well as illuminance to preserve more detail of reflectance while adjusting illuminance. Many suggested Retinex variants can be mentioned such as single-scale Retinex (SSR), Multi-scale Retinex (MSR), and Multi-scale Retinex with capabilities color recovery (MSRCR). However, Retinex-based algorithms are built under manual filters. Therefore, they are not sufficient to handle the complex signal characterization of many different images.

In recent years, deep learning has been widely used in basic image processing and has achieved great success. For example, Dai et al. (2021) proposed a new approach to low-light image

[1]Thuyloi University, 175 Tay Son, Dong Da, Hanoi, Vietnam
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enhancement, which can be adjusted dynamically. Ren et al. introduced a general low-light enhancement and denoising strategy to remove noise inherent in the low-light image enhancement. Although deep learning-based methods have a powerful effect on feature representation, they tend to lose spatial details (such as edges and textures) and amplify noise in dark areas.

Methods based on optimization algorithms have also shown to be effective in improving image quality. For example, Acharya et al. have applied the PSO (Particle Swarm Optimization) optimization algorithm to improve image quality. Kandhway et al. (2020) proposed to use Krill herd optimization (KHO) algorithm to improve the quality of low-contrast images. Some other studies based on optimization algorithms can be mentioned, such as cuckoo search (CS) and SSA (social spider algorithm).

Based on the efficiency that the optimization algorithms bring, we propose a new high-quality image enhancement method based on the MPA optimization algorithm. This method not only enhances the quality of low-light images but also greatly improves the sharpness of the images. Some of our main contributions can be listed as follows:

- Firstly, we propose a new method to decompose the image into two components.

- Second, we propose a new method to improve image quality in low light conditions by using the MPA optimization algorithm.

The rest of the paper is organized in four sections: Section 2 presents background knowledge, such as the MPA optimization algorithm; Section 3 introduces a two-component image decomposition method and a low-light image enhancement algorithm; Experiments and results are presented in section 4; Section 5 presents conclusions and future studies.

2. Background

2.1. YUV model

The YUV model has been widely applied in image processing problems.

The conversion from RGB to YUV model is determined by Eq. (1):

$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.147 & -0.289 & 0.436 \\ 0.615 & -0.515 & -0.001 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

The transformation from the YUV to RGB model is determined by Eq. (2):

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1.000 & 0.000 & 1.140 \\ 1.000 & -0.395 & -0.581 \\ 1.000 & 2.033 & 0.000 \end{bmatrix} \begin{bmatrix} Y \\ U \\ V \end{bmatrix} \quad (2)$$

2.2. MPA optimization algorithm

MPA optimization algorithm Faramarzi et al. (2020) is proposed in 2022. This algorithm has shown its effectiveness in many image processing applications such as medical image fusion (Dinh, 2021, 2022). This algorithm can be described through the following three main stages:

State 1: In the first third of the loop, the prey's moving step size ($\overrightarrow{SS_i}(x,y)$), and its position ($\overrightarrow{Pr_i}(x,y)$) is determined by Eqs. (3) and (4).

$$\overrightarrow{SS_i}(x,y) = \overrightarrow{R_B}(x,y) \otimes \left(\overrightarrow{E_i}(x,y) - \overrightarrow{R_B}(x,y) \otimes \overrightarrow{Pr_i}(x,y)\right) \quad (3)$$

$$\overrightarrow{Pr_i}(x,y) = \overrightarrow{Pr_i}(x,y) + K.\vec{R} \otimes \overrightarrow{SS_i}(x,y) \quad (4)$$

Where

- $\overrightarrow{SS_i}(x,y)$ is a vector containing the moving step size of prey.

- $E(x,y)$ is a matrix built on the fittest solution.

- R is a vector storing random values that follows a uniform distribution.

- K is a constant whose value is 0.5.

- $\otimes$ is the entry-wise multiplication operator.

- $\overrightarrow{R_B}$ is a vector of random numbers generated by the normal distribution.

State 2: In the next third of the loop, the prey's moving step size, and its position is determined by Eqs. (5), (6), (7), and (8).

For the first half of the population:

$$\overrightarrow{SS_i}(x,y) = \overrightarrow{R_L}(x,y) \otimes \left(\overrightarrow{E_i}(x,y) - \overrightarrow{R_L}(x,y) \otimes \overrightarrow{Pr_i}(x,y)\right) \quad (5)$$

$$\overrightarrow{Pr_i}(x,y) = \overrightarrow{Pr_i}(x,y) + K.\overrightarrow{R} \otimes \overrightarrow{SS_i}(x,y) \quad (6)$$

For the second half of the population:

$$\overrightarrow{SS_i}(x,y) = \overrightarrow{R_B}(x,y) \otimes \left(\overrightarrow{R_B}(x,y) \otimes \overrightarrow{E_i}(x,y) - \overrightarrow{Pr_i}(x,y)\right) \quad (7)$$

$$\overrightarrow{Pr_i}(x,y) = \overrightarrow{E_i}(x,y) + K.CF \otimes \overrightarrow{SS_i}(x,y) \quad (8)$$

Where

$$CF = \left(1 - \frac{1}{l_{max}}\right)^{\frac{2*l}{l_{max}}}$$

State 3: In the last third of the loop, the prey's moving step size, and its position is determined by Eqs. (9) and (10).

$$\overrightarrow{SS_i}(x,y) = \overrightarrow{R_L}(x,y) \otimes \left(\overrightarrow{R_L}(x,y) \otimes \overrightarrow{E_i}(x,y) - \overrightarrow{Pr_i}(x,y)\right) \quad (9)$$

$$\overrightarrow{Pr_i}(x,y) = \overrightarrow{E_i}(x,y) + K.CF \otimes \overrightarrow{SS_i}(x,y) \quad (10)$$

Where

- $\overrightarrow{R_L}$ is a vector generated by the Lévy distribution.

Details of the steps of the MPA algorithm are presented in Algorithm (1).

Algorithm 1: MPA algorithm

```
Initialize the required parameters (n, l_max, E, Pr)
Assign parameters: FADs = 0.2; K = 0.5; r in [0,1];
r1 and r2 are random indexes.
U⃗ is the binary vector.
X⃗_min and X⃗_max are the vectors containing the lower and upper bounds.
while l < l_max do
    /* Stage 1: */
    if l < (1/3) l_max then
        Update prey according to Eq. (4);
    end
    /* Stage 2: */
    else if (l > (1/3) l_max) and (l < (2/3) l_max) then
        For the first half of the population.
        Prey is updated according to Eq. (6);
        For the second half of the population.
        Prey is updated according to Eq. (8);
    end
    /* Stage 3: */
    else if l > (2/3) l_max then
        Prey is updated according to Eq. (10);
    end
    /* Eddy formation and FADs' effect */
    if (r ≤ FADs) then
        Pr⃗_i(x,y) = Pr⃗_i(x,y) + CF * ((X⃗_min + R⃗ ⊗ (X⃗_max − X⃗_min)) ⊗ U⃗)
    end
    else if (r>FADs) then
        Pr⃗_i(x,y) = Pr⃗_i(x,y) + (FADs * (1 − r) + r) * (Pr⃗_r1(x,y) − Pr⃗_r2(x,y))
    end
    l = l + 1
end
```

3. The proposed model

3.1. Two-component image decomposition

In this section, we propose a two-component image decomposition (TCID) method. The steps of the algorithm are described as follows:

Input: An image I.

Output: Two components (I_{BL} and I_{DL}).

Step 1: The Gaussian filter is applied to the input image I, obtaining a component (I_{BL}).

Step 2: The detailed component (I_{DL}) is calculated according to Eq. (11)

$$I_{DL} = I - I_{BL} \quad (11)$$

Figure 1 illustrates the input image and components, I_{BL} and I_{DL}, obtained when applying the two-component image decomposition method.

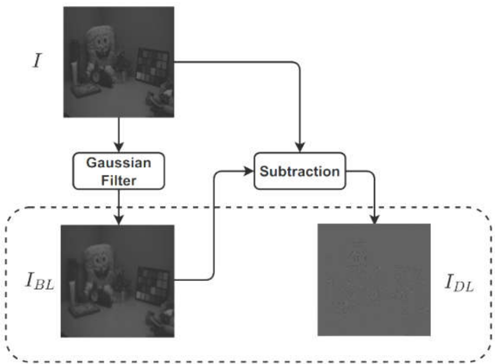

Figure 1. The input image and the two components (I_{BL} and I_{DL}).

3.2. Image enhancement model

Input: Color image I

Output: Enhanced image ($I_{EN_{Color}}$)

The steps are as follows:

Step 1: Input image I is converted to YUV color space, obtaining Y, U, and V channels.

Step 2: Image Y is decomposed into two components (I_{BL} and I_{DL}) by using the TCID method.

Step 3: I_{BL} component is enhanced by the

Local Brightening (LB) method, obtaining I_{LB} component.

Step 4: The Laplacian edge detection operator is applied to the I_{DL} component, obtaining the I_{LED} edge component.

Step 5: Apply the MPA optimization algorithm to find three optimal parameters, β_1, β_2, and β_3. The objective function is described as Eq. (12).

$$F = \frac{V}{M}(E_2 - E_1) \qquad (12)$$

Where

- V is the variance of the I_L image.
- M is the average light intensity of the image I_L.
- E_1 and E_2 are the entropy of Y and I_L images, respectively.
- I_L is the temporally enhanced image computed in each iteration of the MPA algorithm as Eq. (13).

$$I_L = \beta_1 * I_{LB} + \beta_2 * I_{DL} + \beta_3 * I_{LED} \qquad (13)$$

Step 6: The enhanced gray image ($I_{EN_{Gray}}$) is calculated by three optimal parameters (β_1^*, β_2^* and β_3^*) and components (I_{LB}, I_{DL}, and I_{LED}) according to Eqs (14).

$$I_{EN_{Gray}} = \beta_1^* * I_{LB} + \beta_2^* * I_{DL} + \beta_3^* * I_{LED} \qquad (14)$$

Step 7: Three components $I_{EN_{Gray}}$, U, and V are converted to RGB color space, obtaining enhanced color image $I_{EN_{Color}}$.

Figure 2 illustrates the steps in our image enhancement algorithm in detail.

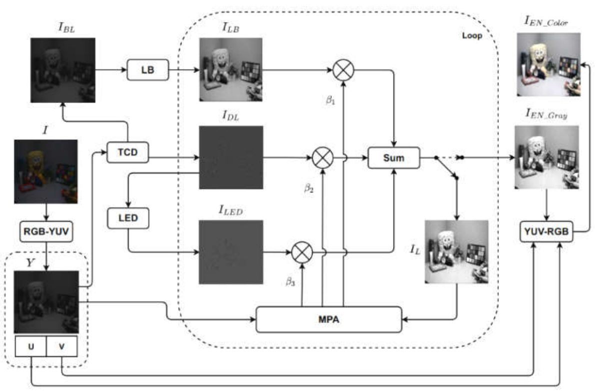

Figure 2. The proposed model

4. Experimental results

4.1. Evaluation indicators

In order to evaluate the images obtained from the proposed method, we use 4 popular metrics including:

- Average light intensity (ALI).
- Contrast Index (CI).
- Entropy (E).
- Sharpness (S).

4.2. Experimental setup

Experimental data are obtained from the source LOL Dataset[2]. We used 95 images for the evaluation. These experimental data are separated into 2 data sets as follows:

- Dataset D1 consisting of 2 random images, is used to evaluate the effectiveness of the MPA algorithm.
- Dataset D2 consisting of 95 images, is used to evaluate the effectiveness of our image enhancement method.

The experiments are set up as follows:

Experiment 1: To explain why to use the MPA algorithm, we choose several other optimal algorithms for comparisons, such as DA (Dragonfly algorithm), ALO (Ant Lion Optimizer), and GWO (Grey Wolf Optimizer). Each optimization algorithm is performed 30 different times. Two metrics, Mean and Standard deviation (SD), are used to evaluate.

Experiment 2: To evaluate the effectiveness of the proposed algorithm, we use some other quality enhancement algorithms for comparison, such as:

- Contrast Limited Adaptive Histogram Equalization (CLAHE)
- Adaptive Gamma Correction With Weighting Distribution (AGCWD)
- Exposure Fusion Framework (EFF) (Ying et al., 2017).

4.3. Experimental results

First, the average value of the objective

[2] https://drive.google.com/file/d/157bjO1_cFuSd0HWDUuAmcHRJDVyWpOxB/view

function after 30 runs with the optimal algorithms is illustrated in Table 1. It is clear that the average index of MPA achieved is the largest, and the obtained SD index is the smallest. This explains why we choose the MPA algorithm.

Table 1. The of values of the optimal function after 30 different runs of the algorithms

Dataset	Algorithms	Mean	Standard deviation
10	SCA	0.394810045539785	0.000183456361529
	SSA	0.394528887449358	0.000390033376000
	GWO	0.394998604036935	0.000013269818726
	MPA	**0.395015923709678**	**0.000000447188703**
100	SCA	1.133359667446346	0.000145579338645
	SSA	1.132774651767913	0.000630092493491
	GWO	1.133641380143254	0.000060075345637
	MPA	**1.133839226052153**	**0.000030115776681**

Second, the experimental results are illustrated in Figure 3 and Table 2. Visually, it is easy to see that the proposed method gives better quality images than the other methods. Quantitatively, from the Table 2, all four indicators of image quality obtained from our proposed method are the highest. This result shows that our method is effective in enhancing low-light images.

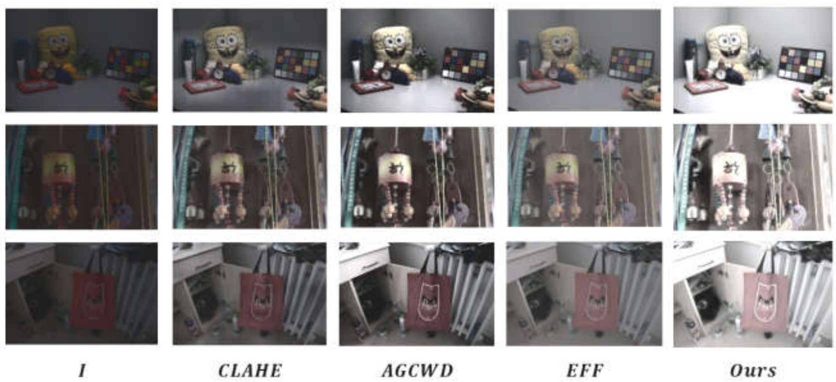

Figure 3. The enhanced image is generated by different image enhancement algorithms

Table 2. Evaluation indexes obtained from enhanced images by image enhancement algorithms

Dataset	Num	Algs	ALI	CI	E	S
D2	1	NE	0.0817	0.0538	5.2480	0.0125
	2	CLAHE	0.1924	0.1137	6.5582	0.0400
	3	AGCWD	0.2978	0.2476	5.2447	0.0640
	4	EFF	0.3075	0.1152	6.5983	0.0353
	5	**Ours**	**0.5666**	**0.2860**	**7.5102**	**0.1079**

5. Conclusion and future work

In this paper, we have proposed a new method to enhance low-light images. First, we propose a two-component decomposition method based on a Gaussian filter. Then, this method is applied to decompose the input image into two components, the base layer (I_{BL}) and the detail layer (I_{DL}). I_{BL} component is enhanced by the Local Brightening

(LB) method, obtaining I_{LB} component. We create one more feature component (I_{LED}) by applying the LED operator to I_{DL}. Then, the MPA algorithm is applied to find the three parameters corresponding to the three components (I_{LB}, I_{DL}, and I_{LED}). Finally, the enhanced image is calculated as the sum of the products of the component multiplied by the corresponding optimization coefficients. Four evaluation indicators, four image enhancement methods, and 95 low-light images were used for comparison. The experimental results show that our proposed method is effective in enhancing image quality.

In the future, we plan to improve the efficiency of our algorithm in two aspects. First, a method is proposed to decompose the image into three components (structure, texture, and noise). This decomposition allows enhancing the image quality by enhancing each component more efficiently. Second, we intend to replace the MPA algorithm with some recently proposed optimization algorithms.

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