Research Article

Noisy Low-Illumination Image Enhancement Based on Parallel Duffing Oscillator and IMOGOA

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In complex environment, the captured images face several kinds of problems, including low illumination and intensive noise, which deteriorates image quality and has a great impact on the follow-up work. In this work, inspired by stochastic resonance theory, we design a model that considers the spatial characteristics of image and noise reduction and enhancement are simultaneously realized. The 8-neighborhood pixel extraction method and the Duffing oscillator model are used to parallel process the image, and then the image details are restored by homomorphic filter. In order to optimize the parameters of parallel Duffing oscillator model and homomorphic filter adaptively, multiobjective grasshopper optimization algorithm is introduced into the method. Sobol sequence and differential mutation operators are used to improve the optimization algorithm, and the fitness function is constructed by using peak signal-to-noise ratio and standard deviation. To verify the effectiveness of the proposed method, low-illumination image data with Gaussian noise is used for subjective and objective evaluation. The experimental results show that the proposed algorithm gives prominence to useful information, which has smaller color distortion and better visual quality.

1. Introduction

An image taken in low-light circumstances, e.g., at night or on a cloudy day, has a low dynamic range and contains noise which degrade the image quality. With more advanced shooting devices and specialized photographic techniques, the quality of captured images may be improved. However, the satisfactory visual effect of images cannot be achieved in the low-illumination environment for hardware limitations. Longer exposure time or stronger auxiliary light are used to improve the contrast and enhance the dark area information of the image partly. Nevertheless, unilateral hardware improvement will lead to new problems, including overexposure and uneven illumination. Imaging quality will be irreversibly affected when there is dust in the air or the sensor noise caused by undesirable lighting and equipment’s high temperature. It directly deteriorates the performance of image processing systems, such as image detection systems, target recognition systems, and visual monitoring systems. Enhancement of low-illumination images becomes more challenging for the noise in images. Therefore, the enhancement method of low-illumination and noisy images has profound theoretical significance and engineering application prospects. Many scholars are also committed to image restoration in complex environments [1–4].

Low-illumination image enhancement is the basis of image processing. Many researchers have been dedicated to low-light image enhancement through innovative and improved algorithms in the past decades. In addition, it also needs to suppress the intensive noises and prevent image blur and distortion while processing low-illumination images. Some Histogram equalization (HE) methods stretch the dynamic range of images [5, 6]. However, their results may present undesirable illumination with image blur and distortion. Wavelet transform methods handle high-frequency and low-frequency subband information separately. Meanwhile, several filters [7, 8] are designed to process the subband information’s contrast and noise. Although the visual quality
of the processed image can be improved partly, it is challenging to realize low-illumination image enhancement under intensive noises. Retinex theory-based methods [9] decompose an image into two components—reflectance and illumination, process these two components separately, and recombine them to obtain the final enhanced results. Many works [10–12] impose priors on the decomposed illumination and reflectance. In [13, 14], the Retinex model is further extended to a robust one with an explicit defined noise term, which benefits developing joint low-light enhancement and noise. In [15, 16], in order to enhance image illumination and avoid color distortion, Camera Response Model is established to find the best exposure.

In recent years, the rise of deep learning has also made momentous contributions to image enhancement. Lore et al. [17] proposed a deep autoencoder-based approach to identify signal features from low-light images to perform brightness enhancement. Wei et al. [18] proposed a Decom-Net for decomposition and an Enhance-Net for illumination adjustment. The Retinex Net is end-to-end trainable, so that the learned decomposition is by nature good for lightness adjustment. Yang et al. [19] improved the Net by building a Restore-Net to restore the reflectance which can be suppress intensive noises and artifacts. Zhao et al. [20] propose that a deep framework is proposed to estimate the latent components and perform low-light image enhancement based on a novel “generative” strategy for Retinex decomposition. Scholars also enhanced the low-illumination image through deep framework and produced a series of low-illumination datasets [21–24]. In addition, CNN is improved to detect ships in complex environments in the application [25]. In these deep learning methods, to enhance low-illumination noisy images, a large amount of data is used to complete the model’s training which cost lots of time.

Some classical theories are also used to construct image enhancement models. Wang et al. [26, 27] introduced the Weber–Fechner law to the grayscale mapping in logarithmic space and proposed a color image enhancement method based on the improved logarithmic transformation, which can adaptively reduce the impact of nonuniform illumination on the image and enhance the image clearly and naturally. And some optimization algorithms have been introduced to increase the contrast of images [28, 29]. In recent years, stochastic resonance theory (SR) based on nonlinear system has been studied widely in weak signal enhancement [30, 31]. It has also received considerable attention in the field of image processing [32–34]. However, the image spatial data needs to be transformed into one-dimensional data in traditional SR methods, which miss spatial characteristics of the processed image.

In order to realize the enhancement and noise reduction of low-illumination noisy images, we propose a parallel image enhancement method based on the nonlinear Duffing oscillator theory and the 8-neighborhood pixel extraction method. This method realizes image enhancement and noise reduction simultaneously, which improves the visualization effect of image information. And, we used IMOGOA to implement parameter adaptive settings for the proposed method. Sobel sequence and differential mutation operators are introduced to improve MOGOA for resolving uneven distribution of model parameter initialization and algorithm convergence accuracy.

Compared with the latest methods, the main contributions of this paper can be summarized as follows:

It is a flexible and effective model to realize image enhancement and noise reduction simultaneously based on nonlinear Duffing oscillator.

In the framework, the parallel Duffing oscillator model is constructed to processing image spatial information. And IMOGOA is introduced to realize adjusting the parameters of the model adaptively.

The 8-neighborhood pixel extraction method is constructed to overcome the lack of spatial information in one-dimensional SR methods. The extracted data are processed by the Duffing oscillator model parallelly, promoting the image enhancement effect, and reducing its fuzzy distortion.

This method does not need lots of datasets for training and can produce satisfying enhancement results on several public datasets, which demonstrate its outperformance.

2. Image Enhancement Method Based on Duffing Oscillator

2.1. Duffing Oscillator Model. Nonlinear Duffing oscillator theory [31] states that noise can effectively drive and stimulate the weak signal when signal and noise are input to the nonlinear system. As for the collected image of low-illumination in a noise environment, its effective information and noise information constitute the input signal, which is processed by a nonlinear Duffing oscillator model. When system parameters satisfy matching conditions, the background noise of the original image has a positive role in the image processing, which is the image SR enhancement theory based on Duffing oscillator model.

Duffing oscillator model can be expressed where Brownian particle repeatedly transitions in a bistable potential well in the presence of noise and periodic forcing. The Langevin equation is often used to describe nonlinear Duffing oscillator models:

\[ \ddot{x} + k\dot{x} = U_{\xi}(x) + s(n), \]  

where \( s(n) \) is the one-dimensional input signal of dimension-reduced image, and \( s(n) = u(n) + \eta(n) \). \( u(n) \) is Gaussian white noise, and \( \eta(n) = \sqrt{2}\xi(n) \) and \( k \) is the damping coefficient. The bistable potential well function is shown in Figure 1, and the equation is

\[ U(x) = -0.5*ax^2 + 0.25*bx^4, \]

where \( x_m = \sqrt{ab} \) and \( x_{-m} = -\sqrt{ab} \) are the bistable potential well position of model, and \( \Delta U = a^2/4b \) is barrier height. The barrier height \( \Delta U \) and barrier distance \( \Delta L \) can be changed by tuning parameters [35].

When mean values of weak target signal \( u(n) \) and noise \( \eta(n) \) of image are zero, the bistable potential well keeps
relative equilibrium in the model. Due to low-illumination image information and noise existing in the collected image, the original equilibrium state in the model will be broken, and the bistable potential well function will bias, which prompts the Brownian particle to undergo periodic transition motion in the bistable potential. At the same time, the particles make a reciprocating transition through the potential barrier by tuning parameters. When stochastic resonance phenomena occur, significantly enhancing image illumination and suppressing noise.

The one-dimensional sequence \( s(n) \) is extracted and normalized from the original image information \( f(x, y) \). The differential equations in the model obtained numerical solution by four-order Runge-Kutta algorithm [36], and the calculation process is described as follows:

\[
\begin{align*}
x_{n+1} &= x_n + \frac{(K_1 + 2K_2 + 2K_3 + K_4)}{6}, \\
y_{n+1} &= y_n + \frac{(L_1 + 2L_2 + 2L_3 + L_4)}{6}, \\
K_1 &= h \cdot y_n \cdot L_1 = h \cdot \left[ a x_n - b x_n^3 - k u_n + s(n) \right], \\
K_2 &= h \cdot \left( y_n + \frac{L_1}{2} \right), \\
L_2 &= h \cdot \left[ a \left( x_n + \frac{K_1}{2} \right) - b \left( x_n + \frac{K_1}{2} \right)^3 - k \left( x_n + \frac{K_1}{2} \right) + s(n) \right], \\
K_3 &= h \cdot \left( y_n + \frac{L_2}{2} \right), \\
L_3 &= h \cdot \left[ a \left( x_n + \frac{K_2}{2} \right) - b \left( x_n + \frac{K_2}{2} \right)^3 - k \left( x_n + \frac{K_2}{2} \right) + s(n + 1) \right], \\
K_4 &= h \cdot \left( y_n + \frac{L_3}{2} \right), \\
L_4 &= h \cdot \left[ a \left( x_n + \frac{K_3}{2} \right) - b \left( x_n + \frac{K_3}{2} \right)^3 - k \left( x_n + \frac{K_3}{2} \right) + s(n + 1) \right],
\end{align*}
\]

where the initial conditions of the solution are set as \( x(0) = \dot{x}(0) = 0 \). \( x_n \) is the \( n \)-th sample value of the image, and \( h \) is the step size of four-order Runge-Kutta algorithm in iteration.

2.2. Image Enhancement Based on Parallel Duffing Oscillator Model. Given the spatial properties of the image, the relationship between each pixel of the image and its surrounding pixels should be considered in image processing, which can achieve better spatial information for the proposed method. Currently, the common pixel extraction methods are Hilbert extraction and column-row extraction. Although the two methods have their advantages in computation and image expression ability, the relation between adjacent pixels is not fully considered. This paper uses the 8-neighborhood pixel extraction method to extract a two-dimensional matrix. Based on the
center pixel, the relationship between each pixel and its neighboring pixels is considered comprehensive. This method is used to reduce the dimensions of image data in four directions of 0 degrees, 45 degrees, 90 degrees, and 135 degrees, separately, as shown in Figure 2. Then the parallel Duffing oscillator model (PDOM) is built to process the data.

Take one channel data of RGB image as an example, assume that the size of the two-dimensional matrix is \( N \times N \), and dimensionality reduction is carried out in four directions. Equations are

\[
S'_{00}(n) = S(i, j)n = (i - 1) \times N + j,
\]

\[
S'_{09}(n) = S(i, j)n = i + (j - 1) \times N,
\]

where \( S'_{00}(n) \) and \( S'_{09}(n) \) represent one-dimensional sequence values extracted in directions of 0 degrees and 90 degrees, respectively. \( S(i, j) \) represents pixel coordinates of a two-dimensional image matrix.

\[
S'_{45}(n) = S(ax, bx),
\]

\[
S'_{135}(n) = S(bx, ax),
\]

where \( S'_{45}(n) \) and \( S'_{135}(n) \) represent one-dimensional sequence values extracted in both directions of 45 degrees and 135 degrees, respectively. \( S(ax, bx) \) and \( S(bx, ax) \) represent pixel coordinates of a two-dimensional image matrix. Here, \( ax = 1, 2, \ldots, y \), \( bx = y, y - 1, \ldots, 1 \), \( y = 1, 2, \ldots, N \), \( n = 1, 4, \ldots, N^2 \).

In this paper, the image enhancement process is mainly divided into three steps. First, the RGB image is decomposed into \( I_R(x, y), I_G(x, y), \) and \( I_B(x, y) \) of a two-dimensional image. And the gray value range of each matrix is normalized to the interval of [0,1]. Then, image data of three channels were input into the parallel Duffing oscillator model. It realizes contrast enhancement and noise suppression of the image data. Take channel \( R \) \( I_R(x, y) \) as an example. The 8-neighborhood pixel extraction method extracts a one-dimensional sequence from \( I_R(x, y) \) and inputs it into the Duffing oscillator model. After the outputs of the model are fused according to the weight coefficient:

\[
\begin{align*}
\dot{x}_1 + kx_1 &= U'(x_1) + S_{00}'(n), \\
\dot{x}_2 + kx_2 &= U'(x_2) + S_{09}'(n), \\
\dot{x}_3 + kx_3 &= U'(x_3) + S_{09}'(n), \\
\dot{x}_4 + kx_4 &= U'(x_4) + S_{135}'(n),
\end{align*}
\]

\[
X(i, j) = \zeta_1 X_1(i, j) + \zeta_2 X_2(i, j) + \zeta_3 X_3(i, j) + \zeta_4 X_4(i, j),
\]

where \( x_1, x_2, x_3, \) and \( x_4 \) represent one-dimensional output sequences of the Duffing oscillator model. \( \zeta_1, \zeta_2, \zeta_3, \) and \( \zeta_4 \) represent fusion weight coefficients of the model. In this paper, the fusion weight coefficients are \( \zeta_1 = 0.3, \zeta_2 = 0.2, \zeta_3 = 0.3, \) and \( \zeta_4 = 0.2 \). \( X_1(i, j), X_2(i, j), X_3(i, j), \) and \( X_4(i, j) \) represent restored images of one-dimensional output sequences according to the original image size. \( X(i, j) \) represents a two-dimensional image which is processed by the model. Meanwhile, the damping coefficient and potential function parameters are used as adjustable parameters for the model and adaptively selected to promote the visual quality and contrast of the output image.

Finally, homomorphic filter is used to enhance the details of the restored image \( X(i, j) \). Fourier transform is used to separate the illumination component \( f_i(x, y) \) and the reflection component \( f_r(x, y) \). Then Gaussian high pass filter \( H(u, v) \) is used to attenuate the low-frequency information and enhance the high-frequency information. After filtering, inverse Fourier transform is carried out to obtain the finished image \( S(x, y) \), i.e.,

\[
X(i, j) = f_i(x, y) + f_r(x, y),
\]

\[
H(u, v) = \left( r_H - r_L \right) \left[ 1 - e^{-c[D^2(u,v)/D_0^2]} \right] + r_L,
\]

\[
S(x, y) = IDFT[H(u, v)f_i(x, y) + H(u, v)f_r(x, y)],
\]

where \( D(u, v) \) represents the distance from the frequency \( (u, v) \) to the filtering center \( (u_0, v_0) \), \( D(u, v) = \sqrt{(u - u_0)^2 + (v - v_0)^2} \). \( r_H = 2 \) is the gain factor of high frequency, and \( c = 1 \) is the sharpening factor. The cut-off frequency \( D_0 \) is an adjustable parameter. Then the homomorphic filter enhances the image’s details and edge information through adaptive parameter selection.

2.3. Performance Evaluation. This subsection compares image denoising and enhancement performance using PDOM and the one-dimensional Duffing oscillator model (ODOM). Five sets of images from the low-light dataset (LOL) and Large-Scale Real-World dataset (LSRW) are selected randomly and respectively. Gaussian noises with mean 0 and variance \( \sigma \in (0.0005 - 0.005) \) are added to the images processed by PDOM and ODOM. Then, the peak signal-to-noise ratio (PSNR) and standard deviation (SD) of the two models’ output can be obtained under different noise levels. To ensure comparability, the initial parameters of the two models are set to the same value. When the noise intensity \( \sigma \) is 0.0005, the promotion value of the PDOM’s PSNR is 8.822 dB, as shown in Figure 3, which is slightly higher than ODOM. However, with the increase in noise.
3. Improved Multiobjective Grasshopper Parameter Optimization Algorithm

3.1. Multiobjective Grasshopper Optimization Algorithm (MOGOA). Grasshopper optimization algorithm is a heuristic optimization algorithm proposed by Saremi et al. [37]. It establishes a mathematical model to approximate the interaction between grasshopper individuals. Mirjalili et al. [38, 39] introduced archive and target technique into the algorithm to solve the multiobjective problem. The algorithm is divided into two parts: exploration and exploitation. In the exploration, individuals move randomly in the whole solution region to find all possible solutions. In the exploitation, individuals search the small probability region due to the inherent information and find the Pareto optimal solution by judging the dominant relationship between solutions. At the same time, the archive is used to store nondominated solutions during the optimization process.

In MOGOA, the position of grasshoppers in the population represents the possible solution to the optimization problem. \( X_i \) is the position of the \( i \)-th grasshopper,

\[
X_i = S_i + G_i + A_i,
\]

where \( S_i, A_i, \) and \( G_i \) separately represent the social interaction, wind advection, and gravity force on \( i \)-th grasshopper.

Social interaction is the main influencing factor of grasshopper movement. Because the effect of gravity on grasshopper population is negligible, and it is assumed that the wind direction is always in the direction of the best individual, the social interaction is described as follows:

\[
S_i = \sum_{j=1, j \neq i}^{N} s(d_{ij})\hat{d}_{ij},
\]

where \( d_{ij} = |x_j - x_i| \) is the distance between \( i \)-th and \( j \)-th of grasshopper, \( \hat{d}_{ij} = (x_j - x_i)/d_{ij} \) is a unit vector from the \( i \)-th grasshopper to the \( j \)-th grasshopper, and \( s(r) = f e^{(-r)} - e^{-r} \) represents social forces of grasshoppers.

Based on the initial definition of gravity and wind for grasshoppers, it determines the accurate approximation of the global optimum. The updated model of grasshopper location can be expressed as

\[
x_i^d = c \left[ \sum_{j=1, j \neq i}^{N} c \frac{u_{b_d} - l_{b_d}}{2} \cdot \sin \left( |x_j^d(t) - x_i^d(t)| \right) \frac{x_j^d(t) - x_i^d(t)}{d_{ij}} \right] + \hat{T}_d,
\]

where \( u_{b_d} \) and \( l_{b_d} \) separately represent the upper bound and the lower bound in the \( d \)-th dimension, and \( \hat{T}_d \) is the position of \( d \)-th dimension in current best solution. Parameter \( c \) is decreasing factor. It increases or decreases with the iterations, affects the algorithm’s global search ability, and improves the local optimization ability. The following formula describes parameter \( c \):

\[
c = c_{\text{max}} - \frac{c_{\text{max}} - c_{\text{min}}}{L},
\]

where intensity, the output PSNR decreases. This phenomenon conforms to the stochastic resonance theory. Figure 4 shows the image enhancement effect, which is evaluated by the standard deviation of the image under different noise intensities. Compared with the traditional ODOM, it can be concluded that PDOM has a better image enhancement effect. Thus, PDOM has better performance in image denoising and image enhancement. Figure 5 shows the details of the low-light image at different noise intensities \( \sigma = 0.002 \). It can be seen that PDOM has better image enhancement and detail information recovery capabilities.

Figure 3: The promoted PSNRs of the image processed by ODOM and PDOM under different noise intensities.

Figure 4: The promoted SDs of the image processed by ODOM and PDOM under different noise intensities.
where \( c_{\text{max}} \) and \( c_{\text{min}} \) separately denote the maximum value and minimum value, and \( l \) and \( L \) separately represent the current iteration and the maximum number of iterations.

### 3.2. Improved Multiobjective Grasshopper Optimization Algorithm (IMOGOA)

IMOGOA is an improved algorithm based on the original algorithm. Firstly, this paper considers the problem of the original algorithm that the initial population distribution was uneven, and the Sobol sequence \([40, 41]\) of low differentiation is used to initialize the population instead of a pseudorandom sequence. Sobol sequence can select the sampling direction reasonably, maximize the quality of the initial population, and avoid local optimum effectively.

Suppose \( X = (x_{ij}) \) is an \( M \times N \) dimensional grasshopper population and \([x_{\text{min}}, x_{\text{max}}]\) is a value range of optimal solution. \( K_n \) is matrix generated by Sobol sequence, \( k_{ij} \in K_n \), and \( k_{ij} \in (0, 1) \). The initial position of the population can be defined as

\[
x_{ij} = x_{\text{min}} + k_{ij} \cdot (x_{\text{max}} - x_{\text{min}}).
\]

At the same time, considering problems of the original algorithm on the convergence accuracy, differential variation operator \([42–44]\) is introduced in this paper, which can improve the diversity of the population and enhance the algorithm ability of the global optimization. The differential mutation operator and individual update formula are

\[
\hat{V}_i(t) = a_0 \left[ r \cdot X_{c_i}(t) + (1 - r) \cdot \left( (X_{c_1}(t) - X_{c_1'}(t)) + (X_{c_2}(t) - X_{c_2'}(t)) \right) \right] + a_1 \cdot X_{c_i}(t),
\]

\[
x_i^d(t) = c \cdot \left[ \sum_{j=1, j \neq i}^{N} c \frac{ub_d - lb_d}{2} s \left( x_i^d(t) - x_j^d(t) \right) \right] \cdot \frac{x_i(t) - x_j(t)}{d_{ij}} + \hat{V}_i(t),
\]

where \( a_0 \) and \( a_1 \) are the scaling factors and range from 0 to 2. And \( r \) is a random number ranging from 0 to 1. \( X_{c_i}(t) \) is an individual selected from the sparse region of solutions with large probability. \( X_{c_1}(t) \) and \( X_{c_2}(t) \) are individuals selected from the dense region of solutions with large probability. \( X_{c_i}(t) \) is an individual randomly selected from the current solutions. \( X_{c_1}(t) \), \( X_{c_2}(t) \), and \( X_{c_3}(t) \) make up a difference mutation operator, and it realizes the exchange of dominance information among individuals. The difference mutation operator can also improve the global optimization ability of the algorithm, help the algorithm avoid the local optimization, and improve the convergence accuracy. Meanwhile, \( X_{c_i}(t) \) can increase the randomness of variation and avoid achieving a premature convergence of optimal local solutions.

### 4. Image Enhancement Based on PDOM and IMOGOA

In this paper, IMOGOA is used for adaptive optimization of parameters \( a, b, k, \) and \( D_0 \) of the proposed method.

![Image](image.png)

**Figure 5**: The detail of the low-light image processed by ODOM (a, c, e, g) and PDOM (b, d, f, h) (\( \sigma = 0.002 \)).
4.1. Fitness Function. The image’s standard deviation (SD) and peak signal-to-noise ratio (PSNR) are used to construct the fitness function. The larger the SD of the image, the richer the image information and the greater the image contrast. The larger the PSNR of the image, the less the image noise and distortion.

\[
SD = \sqrt{\frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (X_{ij} - u)^2},
\]

\[
MSE = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \|X(i, j) - O(i, j)\|^2,
\]

\[
PSNR = 10 \log \left( \frac{MAX^2}{MSE} \right),
\]

where \( M, N \) represent the number of rows and columns of the image, \( u \) represents the pixel mean value, and \( X_{ij} \) represents the output image pixel value. \( X(i, j) \) and \( O(i, j) \) separately represent the output image and the original image, and \( MAX \) is 255, meaning the largest gray level.

4.2. Algorithm Flow. The image enhancement algorithm based on parallel Duffing oscillator and IMOGOA is shown in Figure 6. The specific steps of the algorithm are as follows:

Step 1: The input image to be processed. Parameters are initialized, including population size, external solution size, the number of iterations, the maximum number of iterations, and the decreasing factor. Sobol sequence is used to initialize population, which are the parameters \( a, b, k \), and \( D_0 \). Meanwhile, an empty external solution \( Pa \) is built.

Step 2: The parameters \( a, b, k \), and \( D_0 \) are substituted into the Duffing oscillator model. The fitness function calculates the fitness value, and nondominated solutions are found and stored in \( Pa \).

Step 3: The parameter \( c \) is updated according to equation (11). The differential mutation operator is calculated by equation (13). The individual position of the population is updated according to equation (14).

Step 4: Whether the current number of iterations is greater than the maximum number of iterations. If it is true, the algorithm ends. Otherwise, it repeats step 2 and step 3 and updates the number of iterations.

Step 5: A group of optimal parameter values is randomly selected from \( Pa \) and substituted into the Duffing oscillator enhancement method. Finally, the final enhanced image is output.

5. Experimental Results and Analysis

LOL dataset and LSRW dataset both contain images with low and normal illumination. Therefore, in this paper, their images are selected as the data samples for the experimental simulation to prove the algorithm’s effectiveness. First, the subjects are four low-illumination images selected from the LOL dataset, and Gaussian noise with intensity of \( \sigma = 0.001 \) is added to them. They are, respectively, named A, B, C, and D. The subjects are three low-illumination images selected from the LSRW dataset, and Gaussian noise with the intensity of \( \sigma = 0.001 \) is added to them. They are, respectively, named E, F, and G. Then, images are processed separately by the proposed algorithm and other methods. In this study, the population size, the external solution size, and the maximum number of iterations are set as 50. We qualitatively and quantitatively compare our method with several advanced methods, including Histogram Equalization (HE), Low-Illumination Map Estimation (LIME) [11], Camera Response Model (CRM) [15], Hybrid Optimization Contrast Enhancement (HOC) [29], Semidecoupled Decomposition Retinex (SDR) [13], and Deep Retinex Decomposition Net (Retinex Net) [18]. Then, Figures 7–13 are the experimental results of Figures A, B, C, D, E, F, and G, respectively.

5.1. Subjective Visual Evaluation. Although the contrast of the original images is improved to some degree and their overall visibility is improved significantly, the effect of image
Figure 7: Enhancement of image A: (a) noise-free image under normal lighting; (b) original noisy low-illumination image; (c) HE; (d) LIME [11]; (e) CRM [15]; (f) HOC [29]; (g) SDR [13]; (h) Retinex Net [18]; (i) the proposed algorithm.

Figure 8: Enhancement of image B: (a) noise-free image under normal lighting; (b) original noisy low-illumination image; (c) HE; (d) LIME [11]; (e) CRM [15]; (f) HOC [29]; (g) SDR [13]; (h) Retinex Net [18]; (i) the proposed algorithm.

Figure 9: Enhancement of image C: (a) noise-free image under normal lighting; (b) original noisy low-illumination image; (c) HE; (d) LIME [11]; (e) CRM [15]; (f) HOC [29]; (g) SDR [13]; (h) Retinex Net [18]; (i) the proposed algorithm.
Figure 10: Enhancement of image D: (a) noise-free image under normal lighting; (b) original noisy low-illumination image; (c) HE; (d) LIME [11]; (e) CRM [15]; (f) HOC [29]; (g) SDR [13]; (h) Retinex Net [18]; (i) the proposed algorithm.

Figure 11: Enhancement of image E: (a) noise-free image under normal lighting; (b) original noisy low-illumination image; (c) HE; (d) LIME [11]; (e) CRM [15]; (f) HOC [29]; (g) SDR [13]; (h) Retinex Net [18]; (i) the proposed algorithm.

Figure 12: Enhancement of image F: (a) noise-free image under normal lighting; (b) original noisy low-illumination image; (c) HE; (d) LIME [11]; (e) CRM [15]; (f) HOC [29]; (g) SDR [13]; (h) Retinex Net [18]; (i) the proposed algorithm.
noise suppression is not apparent. As shown in Figures 7, 8, 11, and 12, the image quality is partly enhanced by SDR and Retinex Net, and the image illumination is not significantly improved due to the covering noise. In addition, Retinex Net can amplify the noise in dark areas. HE and HOC can achieve good results in contrast enhancement. However, the illumination of the processed image becomes stronger, which directly leads to a distorted enhanced image and partial area information loss of the image. As shown in Figures 9 and 10, these algorithms can achieve good overall quality in illumination. However, CRM and Retinex Net produce a high noise level, and partial area information is covered. The image processed by LIME has severe hue deviation and color distortion. The proposed algorithm can obtain better results than others in terms of color recovery and brightness enhancement. The overall visibility and contrast of the image are improved, and noise is better suppressed than other methods, which leads to a good visual effect.

5.2. Objective Quantitative Analysis. Different methods have different image enhancement focuses, so sufficient objectivity is difficult to achieve in a subjective assessment. Therefore, an objective assessment is performed to further assess the selected algorithms’ effectiveness using peak signal-to-noise ratio (PSNR) and standard deviation (SD). The larger the PSNR of the image, the less the image distortion and the better the noise suppression. The larger the SD of the image, the richer the information and the higher the contrast of the image.

From Table 1, we can see that, after processing by our method, the PSNR of Image A, C, E, and F is increased, 11.0643 dB more than the PSNR of the original noisy low-illumination image on average. It is higher than HE, CRM, and LIME and far higher than SDR, Retinex Net, and HOC algorithm in PSNR. It shows that the proposed algorithm has less noticeable distortion and can obviously suppress noise. As for Image G, its PSNR has been significantly improved only by SDR and the proposed algorithm. Other algorithms’ results are unsatisfactory because the noise has not been effectively suppressed. As for Image B and Image D, our method is not superior to other methods in the PSNR promotion. It is mainly because Figure 8(a) and Figure 10(a) have poor color performance and low contrast. However, the enhanced images by our method have more saturated color and better visibility than other methods. From the image evaluation data of each group, we can see that the image enhanced by the proposed algorithm is 40.7285 higher than the original image in SD. Although its SD does not reach the maximum of seven algorithms, the contrast can be maintained at an appropriate level. Furthermore, it shows that the image processed by the proposed algorithm can keep the illumination enhancement effect, and the original feature information and details of the image are preserved.

5.3. Adaptivity Analysis. In order to reflect the adaptability of the algorithm under different environment, experiments are carried out using the proposed method on images under different illumination conditions. The results are shown in Figures 14–16. The first row contains the unprocessed images (a, b, c, and d), while the second row contains the improved images (e, f, g, and h). Figures 14(e) and 14(f) show the enhancement of backlight image with noise. The contrast of dark areas is improved; however there is a slight overenhancement of the bright areas in the image, which causes the brightness deviation between the bright area and dark area of the image. Hence the local information of bright area and dark area of the image should be considered in the enhancement processing. Figures 14(g) and 14(h) show the enhancement of hazy images at night, and Figures 15(e)–15(h) show the enhancement of hazy images in day time. They show that the proposed method can enhance the details of the hazy images, but the contrast of the enhanced images will be reduced for the large gray value of the original. Therefore, only the method combined with defogging can achieve satisfactory results. Figures 16(e)–16(h) show the enhancement of underwater image. The contrast of image is improved, but color recovery effect of this method is unsatisfactory. Figures 16(e) and 16(f) have better effect after
processing which are consistent with human visual perception. Figures 16(g) and 16(h) have obvious distortion, and the color performance is quite different from the original image. Further color restoration algorithms are needed to improve the visibility of images. Overall, the proposed method can be adaptively suitable for different scenes and has excellent robustness, but some aspects should be considered for some special scenes.

5.4. Computational Complexity. In the method, the core algorithm is the Duffing oscillator model which is a nonlinear equation and should be solved numerically. In this paper, the fourth-order Runge–Kutta method is used to solve the model, which is time-consuming and has a large impact on the overall runtime of the method. Therefore, the computational complexity of the proposed method PDOM is considered in this part. We use 400 × 600-pixel images to carry out experiments in MATLAB 2021 on CPU (Intel Core-i7). The average runtime needed for 20 operations on the same image size is taken as the runtime of that size image. PDOM takes 2.354 s to process a 400 × 600-pixel image. With the increase in the size of the images, the time-consuming proportion of PDOM increases. Hence, the

| Image name | Metric | Input | HE  | LIME | CRM  | HOC  | SDR  | Retinex Net | Ours  |
|------------|--------|-------|-----|------|------|------|------|-------------|-------|
| Image A    | PSNR (dB) | 7.221 | 16.310 | 12.956 | 13.501 | 13.333 | 11.388 | 11.397 | 20.040 |
|            | SD     | 23.381 | 64.994 | 55.795 | 45.135 | 86.513 | 38.384 | 39.585 | 74.400 |
| Image B    | PSNR (dB) | 10.923 | 8.653 | 12.869 | 14.887 | 7.699 | 14.934 | 12.507 | 13.274 |
|            | SD     | 6.770 | 47.698 | 47.625 | 35.127 | 79.388 | 18.847 | 36.590 | 67.126 |
| Image C    | PSNR (dB) | 10.329 | 14.474 | 13.670 | 14.693 | 9.818 | 16.494 | 13.179 | 20.691 |
|            | SD     | 30.779 | 67.677 | 58.940 | 46.606 | 83.867 | 44.915 | 40.151 | 61.692 |
| Image D    | PSNR (dB) | 10.450 | 12.775 | 15.450 | 17.299 | 14.784 | 18.672 | 16.442 | 12.331 |
|            | SD     | 12.943 | 64.372 | 49.536 | 37.201 | 59.473 | 28.935 | 32.382 | 53.113 |
| Image E    | PSNR (dB) | 5.835 | 14.501 | 12.501 | 13.880 | 13.297 | 9.682 | 10.960 | 16.568 |
|            | SD     | 12.548 | 65.530 | 49.975 | 45.569 | 80.826 | 28.495 | 37.665 | 74.696 |
| Image F    | PSNR (dB) | 8.594 | 13.686 | 13.590 | 15.305 | 10.380 | 12.969 | 12.258 | 18.937 |
|            | SD     | 23.342 | 62.635 | 56.958 | 50.179 | 88.778 | 38.193 | 41.711 | 54.996 |
| Image G    | PSNR (dB) | 11.689 | 12.775 | 13.177 | 14.926 | 11.392 | 17.771 | 14.199 | 19.444 |

Table 1: The assessment results of images.

| Image name | Input | HE  | LIME | CRM  | HOC  | SDR  | Retinex Net | Ours  |
|------------|-------|-----|------|------|------|------|-------------|-------|
| Image A    | 18.922 | 18.101 | 17.261 | 14.815 | 23.038 | 14.698 | 30.777 |
| Image B    | 11.029 | 9.278 | 13.276 | 6.109 | 30.406 | 8.013 | 33.509 |
| Image C    | 17.321 | 17.073 | 18.644 | 10.599 | 22.614 | 16.022 | 31.173 |
| Image D    | NaN  | 19.305 | 20.278 | 19.350 | 20.294 | 21.902 | 16.197 | 33.449 |
| Image E    | 5.520 | 2.030 | 8.963 | 2.769 | 19.923 | 1.586 | 24.269 |
| Image F    | 8.901 | 10.077 | 11.9912 | 5.583 | 24.496 | 9.300 | 26.888 |
| Image G    | 21.663 | 21.674 | 22.4193 | 19.933 | 28.514 | 21.014 | 30.977 |

Table 2: The NILEE [43] value of images.

Figure 14: Enhancement of images under complex environment.
future work should focus on reducing the computational complexity of PDOM.

6. Conclusions

This paper proposes a method that realizes image enhancement and denoising for low-illumination and noisy images based on parallel Duffing oscillator and improved multiobjective grasshopper optimization. Compared to other algorithms, the PSNR of the image enhanced by the proposed algorithm increased by 30% on average, and its SD is 3.3 times higher than the original noisy low-illumination image. In addition, the proposed method's average NILEE comprehensive evaluation value is 31.594, which is also significantly better than the other methods. The method uses an 8-neighborhood pixel extraction method to reduce the dimensions of two-dimensional image data and constructs a parallel Duffing oscillator model to process the image data. And it restores image details using homomorphic filtering. Computational complexity is a limitation of the method, leading to longer runtime of a single image and lower real-time performance. Overall, the proposed algorithm in this paper has better image enhancement effects, less color distortion, and richer image details, which can suppress noise effectively and enhance illumination.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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