Martial Art Learning Optimization: A Novel Metaheuristic Algorithm for Night Image Enhancement

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Abstract

This paper proposes a human behavior-based optimization algorithm, Martial Art Learning Optimization (MALO), for optimization problems in continuous spaces. The algorithm simulates the process of characters in martial arts learning so as to apply it to optimization problems. Characters in martial arts stories usually go through multiple stages of learning martial arts, such as self-study and leader teaching. Multiple learning stages of characters are modeled in this paper, utilizing the wisdom of the characters learning martial arts in the novel, enabling the optimization process. To verify and analyze the performance of the proposed algorithm, the algorithm is numerically tested on 30 benchmark functions, and it is found that its performance was better than the state-of-the-art nine algorithms. In addition, the algorithm is also used to solve the problem of nighttime image brightness enhancement. Compared with other image enhancement methods, the proposed MALO algorithm has superior results in both visual effects and quantitative image quality assessments.

Keywords: Martial Art Learning Optimization, Swarm intelligence, Metaheuristic, Image enhancement

1 Introduction

The optimization problem refers to finding the optimal solution or parameter value among many solutions or parameter values under certain conditions so that some system performance indicators can reach the maximum or minimum value. Optimization processing has been widely used in many fields, such as signal processing, image processing, production scheduling, task allocation, pattern recognition, automatic control and mechanical design. It has produced enormous economic and social benefits. Optimization methods have come a long way in the past few decades.

Metaheuristic algorithm is a commonly used method to solve global optimization problems. It mainly achieves the solution of the optimal solution by simulating nature or human intelligence and gives a feasible solution to the problem at an acceptable cost. The method is divided into two stages, exploration and exploitation. In the exploration stage, the algorithm searches the entire space as much as possible, looking for potential areas. During the exploitation stage, the algorithm carefully searches promising areas to find the optimal solution. Metaheuristic optimization algorithms are generally divided into four categories, evolution-based, swarm intelligence-based, physical and math rule-based, and human behavior-based algorithms. The evolution-based algorithm is constructed on the pattern of the survival of the fittest in the process of inheritance, selection, and mutation. The most classic algorithms are Genetic Algorithm (GA) [1] and Differential Evolution (DE) [2]. The optimization algorithm based on swarm intelligence is produced by the behavioral laws of biological groups. It is inspired by social insects (e.g., ants, bees) and social animals (e.g., flocks of birds, fish, and herds) to solve optimization problems. In the past few decades, many algorithms with superior performance have emerged in the field of swarm intelligence optimization, such as Particle Swarm Optimization (PSO) [3-5], Cat Swarm Optimization (CSO) [6], Grey Wolf Optimizer (GWO) [7], Ant Colony Optimization (ACO) [8], Salp Swarm Algorithm (SSA) [9-10], Slime Mould Algorithm (SMA) [11], Bat Algorithm (BA) [12], Fish Migration Optimization (FMO) [13-14], Aquila Optimizer (AO) [15], Phasmatodea Population Evolution algorithm (PPE) [16], Gannet Optimization Algorithm (GOA) [17], Tumbleweed Algorithm (TA) [18], Golden Jackal Optimization (GJO) [19]. Physics-based algorithms usually mimic the rules of physics to achieve optimization, such as Gravitational Search Algorithm (GSA) [20], Black Hole algorithm (BH) [21], Big Bang–Big Crunch (BB–BC) [22], Henry Gas Solubility Optimization (HGSO) [23], Quantum Approximate Optimization Algorithm (QAOA) [24], Equilibrium Optimizer (EO) [25-26], Gradient-Based Optimizer (GBO) [27], Sine Cosine Algorithm (SCA) [28]. Human behavior-based algorithms are mainly inspired by human social behavior. The main algorithm is Teaching-Based Optimization (TLBO) [29], which simulates the teaching behavior of teachers and the learning behavior of students. In addition, there are Soccer League Competition algorithm (SLC) [30], Exchange Market

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Algorithm (EMA) [31], Brain Storm Optimization (BSO) [32], Gaining Sharing Knowledge based Algorithm (GSK) [33], Political Optimizer (PO) [34].

Although both traditional and recent metaheuristic algorithms have been successful to a certain extent, they are still not guaranteed to find the global optimum for all optimization problems. And as the optimization problem becomes increasingly complex, the existing optimization algorithms can no longer fully function. The proven No Free-Lunch (NFL) [35] theory has prompted many researchers to design a new algorithm and solve new classes of problems more efficiently. Therefore, a new algorithm based on human behavior is proposed in this paper, which is called Martial Art Learning Optimization (MALO). It finds the optimal value in the solution space by simulating the way characters in Chinese chivalry novels learn martial arts.

Images captured at night are affected by the shooting environment and insufficient surrounding brightness. The captured images generally have shortcomings, such as low brightness and lack of details, which make it impossible for observers and subsequent image processing systems to recognize and process them. Therefore, it is a problem that must be solved to enhance the night image, improve its brightness and contrast, and make the details more clear. Image enhancement is considered a nonlinear multimodal optimization problem and thus can be solved with metaheuristics [36]. In this paper, in addition to verifying the performance of the proposed algorithm using benchmark functions, the proposed MALO algorithm is also used to solve the image enhancement problem.

The rest of the paper is organized as follows: Section 2 expounds on the concepts and sources of inspiration for MALO and details the execution of the algorithm. Section 3 compares the performance of the algorithms and conducts comprehensive tests on 30 benchmark functions. In Section 4, the algorithm proposed is applied to the parameter optimization of nighttime image enhancement. Finally, conclusions and future works are presented in Section 5.

2 Martial Art Learning Algorithm

This section introduces the multiple stages of the characters in martial arts novels learning martial arts. Mathematical modeling is carried out based on this inspiration, and an optimization algorithm for martial arts learning is proposed.

2.1 Inspiration and Elicitation

Louis Cha is almost unknown in China, and many of his works are adapted into TV series, movies, and video games. In the martial arts novels of Louis Cha, a person needs to go through multiple stages to obtain powerful martial arts. The protagonist in the book becomes the person with the highest combat force only after going through many difficulties and obstacles. Martial arts are like other skills in real life and requires constant study and practice to acquire. But in the world created by Louis Cha, the concept of martial arts has an extra layer of fantasy. In the book *The Smiling, Proud Wanderer*, there is a star-sucking Dafa practiced by a character that can absorb the internal strength of others to enhance himself. The Sunflower Manual, a martial art, requires practitioners to castrate themselves before practicing the skills in the manual. In *The Legend of the Condor Heroes*, the protagonist cultivates the Eighteen Dragon Subduing Palms, which combines hardness and softness, and is powerful. The Nine Yin Skeleton Claw practiced by the character Cyclone Mei can make people's fingers as hard and powerful as steel and can be used directly as weapons to attack the enemy.

In the martial arts world described by Louis Cha, martial arts manoeuvers can be all-encompassing and ever-changing. In martial arts novels, characters acquire this skill in different ways. Some characters need to learn from a teacher, and some acquire the books on this skill by chance and become self-taught. And some villains directly seize the skills of other people through unconventional means.

The experience and wisdom of characters learning martial arts in novels can be used to solve the optimization problem. The following sections describe how these processes are mathematically modeled.

2.2 Mathematical Model

In this part, the various stages of learning martial arts will be described in detail with mathematical models.

2.2.1 Self-learning Stage (Exploration)

When a character first enters a gang, he has not yet been exposed to the core educational resources of the gang, so he can only explore on his own and gain experience by watching others practice so as to learn. Characters can learn from the learning methods of those with stronger force around them. This learning process can be described mathematically as:

$$X_{new1} = X_i + a * (X_M - X_i) + |Levy(D)| * (X_b - X_i), \quad \textbf{(1)}$$

where X_i is the i-th individual in the population. a represents the learning tendency and is a non-monotonic function that will change from 1 to 0, the change process is shown by Equation 2. X_M represents the position mean of the solution in the entire population. D is the dimension of the solution. $Levy(D)$ is the Levy flight distribution function, which represents some improvements made by the character in combination with his situation after learning from the experience of the strong. X_b represents the optimal solution in the current iteration of the population.

$$a = \left(1 - \frac{t}{T_{\max}}\right) * \sin\left(\frac{3\pi}{5} + \sin\left(\frac{3\pi}{5} * \left(1 - \frac{t}{T_{\max}}\right)\right)\right) * \frac{5}{3} * 2, \quad \textbf{(2)}$$

where t represents the current iteration number. $T_{\max}$ represents the total number of iterations during the execution of the algorithm. The change process of a is as shown in Figure 1 shown.

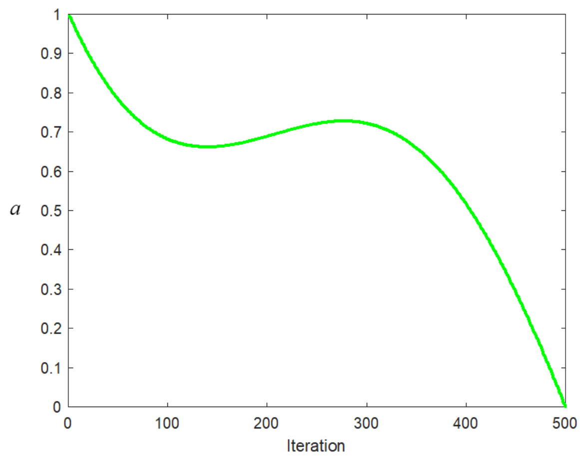


Figure 1. Curve of parameter *a* affected by iteration

In addition, characters in the novel can also learn from the failure of the weaker to self-correct and learn. This process can be described by the following mathematical equations.

$$X_{new2} = X_{rand} + a * (X_i - X_w), \tag{3}$$

where X_{rand} is a randomly generated solution defined as Equation 4 shown. X_w represents the worst solution of the population in the current iteration.

$$X_{rand} = LB + rand * (UB - LB), \tag{4}$$

where *UB* and *LB* represent the upper and lower bounds of the solution, respectively. *rand* is a random number in the [0, 1].

2.2.2 Leader Teaching Stage (Exploitation)

At this stage, the character has been studying in the gang for a while and is already the direct disciple of the head of the gang. As the person with the highest force value in the gang, the gang leader will teach students according to the characteristics of their disciples, and pass on their skills to their disciples after appropriate modifications. This process can be described by the following mathematical equations.

$$X_{new3} = X_b * \beta + a * \frac{\|X_{r1} - X_{r2}\|_2}{\|X_b - X_w\|_2} * X_{rand}, \tag{5}$$

where *beta* represents the impact factor of teaching, which is determined by the Equation 6 definition. $\|\cdot\|_2$ represents the L2 norm.

$$\beta = e^{\frac{X_i - X_w}{\|X_b - X_w\|_2}}. \tag{6}$$

For disciples with poor aptitude, the master needs to make too many revisions to his skills before teaching them to the disciples, to prevent the disciples from going wrong while practicing. The following equation describes this process.

$$X_{new4} = X_b * |Levy(D)| + a * (X_i - X_M). \tag{7}$$

2.2.3 Learning Mode Selection Stage

At this stage, once the character finds that his practice skills have deteriorated, he will replace his previous learning mode and choose a new method. In order to express more conveniently, an operation bit is added to the dimension of the solution to indicate which mode of learning martial arts is selected. The solution is represented by the Equation 8 shown.

$$X_i = \{x_{i,1}, x_{i,2}, ..., x_{i,d}, op\}, \tag{8}$$

where *d* is the true dimension of the solution in the optimization problem. The last bit *op* of the solution is the operation bit, which represents the learning mode adopted by the character. The learning mode selection process in the self-learning and leader teaching stage can be described by the following two equations respectively.

$$X_i = \begin{cases} X_{new1}, & op = 0 \\ X_{new2}, & op = 1 \end{cases}. \tag{9}$$

$$X_i = \begin{cases} X_{new3}, & op = -1 \\ X_{new4}, & op = 2 \end{cases}. \tag{10}$$

In the self-learning stage, the value of the operand bit can only be 0 or 1. In the leader teaching stage, its value can only be -1 or 2.

If the fitness of the solution in this iteration process is worse than the previous one, then assign the operation bit to another value, otherwise, the operation bit of the current solution remains unchanged. This process can be described in the following equation.

$$op = 1 - op, fit(X_i^t) \geq fit(X_i^{t-1}), \tag{11}$$

where the optimal problem is defined as a minimization problem. *fit* represents the fitness value of the solution.

2.2.4 Gang Communication Stage

At this stage, gangs are first defined. The total population is divided into *n* gangs, and each gang g_i consists of *m* members. The gang is represented by the Equation 12 shown.

$$g_i = \{X_1, X_2, ..., X_m\}. \tag{12}$$

In martial arts novels, there will be a competition for martial arts leaders every few years. Different gangs will conduct martial arts competitions to select the most powerful people. Participants can also gain experience in martial arts competitions and improve their martial arts. This process is shown in Equation 13.

$$X^* = \min(g_1^*, g_2^*, ..., g_n^*), \tag{13}$$

where n means that the entire population is divided into n gangs. X^* indicates the individual with the highest combat effectiveness in this population. g_1^* means the person with the highest fighting power in the gang g_1, which is also the leader of the gang. After the martial arts leader is elected, the head of the gang will learn from the martial arts leader every few years.

$$g_i^* = X^*,\ i = 1, 2, ..., n. \quad \textbf{(14)}$$

It should be noted that X_b and X_w in Equation 1-7 are the best and worst individuals in the gang, respectively.

2.2.5 Re-practice Stage

In the process of practicing martial arts, the character is likely to go crazy and enter a very unstable state. It is also the bottleneck period of martial arts practice. If a solution gets stuck in a local optimum during optimization, it can be defined as entering a bottleneck period. In this case, the 20% individuals with poor fitness values in the gang can be reassigned to 0 or 1 to re-enter the self-learning stage.

The pseudo-code of MALO is shown in Algorithm 1.

Algorithm 1. Pseudo-code of MALO

```
Input: The number of gangs n, the number of members in the gang m, and the maximum number of iterations T_max
Output: The optimal individual X* in the population and its fitness value
Initialize the population position X, and divide it into n gangs
Set op is 0 or 1 and calculate the fitness value
Select the leader of each gang and the individual with the worst force
while t ≤ T_max do
    for each gang do
        for each member of the gang do
            if t%10==0 then
                Enter gang communication and re-practice stage
            end if
            if t ≤ (3/5) T_max then
                Update position by Equation 1-4 and Equation 9
            else
                Update position by Equation 5-7 and Equation 10
            end if
            Calculate the fitness value of each solution
            Update op of solution by Equation 11
        end for
        Pick out X_b and X_w within each gang
    end for
    Pick out X* by Equation 13
    t=t+1
end while
return X*
```

3 Experimental Results and Analysis

The performance of MALO algorithm is tested in this section. It compares with numerous metaheuristic algorithms on 30 benchmark functions. These functions include unimodal function, multimodal function, hybrid function, and composite function. To avoid contingency, each algorithm is run independently 30 times. The code for algorithm comparison is done on MATLAB R2017a. The whole experiment is performed on Windows 10 system and the CPU is Intel (R) Core(TM) i3-8100(3.60GHz).

3.1 Benchmark Function and Parameter Settings

In this section, MALO is evaluated on 30 benchmark functions of CEC2017 [37-38]. All benchmark functions include 3 unimodal functions (F1-F3), 7 multimodal functions (F4-F10), 10 hybrid functions (F11-F20), and 10 composite functions (F21-F30). To verify the performance of the proposed algorithm, MALO is compared with several meta-heuristic algorithms, including SSA [9], SCA [28], PSO [5], BA [12], GA [1], GJO [19], TA [18], and PO [34]. The parameters of these algorithms are set in Table 1 shown. The evaluation times of the fitness function of all algorithms are 30000 times. NP in the table represents the population size. Others parameters are based on the parameters used by the original author in the article or the parameters widely used by various researchers. Two statistical metrics, average (AVG) and standard deviation (STD), are used to evaluate the result of the algorithms.

Table 1. Parameter settings for the algorithms involved in the comparison

Algorithm	Parameters setting
SSA	NP=50
SCA	NP=50, a=2
PSO	NP=50, c_1=2, c_2=2
GA	NP=50, crossover rate=0.7, mutation rate=0.2
BA	NP=50, A=0.5, r=0.5
GJO	NP=50, c_1=1.5
TA	NP=50
PO	NP=49, n=7, λ=1
MALO	NP=50, n=5

3.2 Comparison with Other Algorithms

Table 2 to Table 3 show the experimental results of the algorithms in 30-dimension and 50-dimension respectively, and the optimal results under each function are shown in bold. The last row of the table summarizes the number of MALO wins compared to other algorithms.

Table 4 makes statistics on the winning of different algorithms on 30 functions. It can be seen in Table 4, that when the dimension of the solution is 30, among the nine metaheuristic algorithms comparison, MALO is still the best performing algorithm, and it wins 16 functions on the 30 benchmark functions. The overall performance of MALO is better than that of SSA, SCA, PSO, BA, GA, GJO, TA, and PO on the comparison of 30 benchmark functions in CEC2017.

Table 2. Comparison results of multiple algorithms when D=30

Function		MALO	SSA	SCA	PSO	BA	GA	GJO	TA	PO
F1	AVG	4.21E+03	**3.63E+03**	1.85E+10	8.49E+06	8.34E+10	2.26E+10	1.02E+10	1.90E+08	1.22E+07
	STD	4.28E+03	**3.34E+03**	3.07E+09	2.74E+06	1.53E+10	2.15E+09	2.63E+09	1.61E+08	5.24E+07
F2	AVG	**3.56E+18**	3.27E+19	4.33E+36	3.55E+26	4.52E+53	1.31E+41	2.27E+33	9.25E+26	7.54E+25
	STD	**1.00E+19**	9.65E+19	1.13E+37	1.59E+27	1.76E+54	5.69E+41	4.23E+33	1.99E+27	2.53E+26
F3	AVG	5.33E+04	3.48E+04	7.24E+04	**6.84E+03**	3.35E+05	6.13E+04	5.42E+04	5.56E+04	6.77E+04
	STD	9.28E+03	1.01E+04	1.09E+04	**2.63E+03**	1.10E+05	7.42E+03	1.03E+04	1.06E+04	3.52E+03
F4	AVG	5.19E+02	5.03E+02	2.50E+03	5.15E+02	2.16E+04	5.73E+03	1.16E+03	6.79E+02	**5.00E+02**
	STD	**1.16E+01**	2.18E+01	8.73E+02	2.72E+01	5.42E+03	7.39E+02	7.73E+02	8.88E+01	1.38E+01
F5	AVG	5.94E+02	6.76E+02	8.12E+02	6.77E+02	8.77E+02	8.18E+02	7.13E+02	7.19E+02	**5.93E+02**
	STD	3.62E+01	5.65E+01	**2.15E+01**	2.52E+01	6.08E+01	2.35E+01	5.33E+01	5.35E+01	3.36E+01
F6	AVG	6.06E+02	6.51E+02	6.60E+02	6.56E+02	6.80E+02	6.72E+02	6.35E+02	6.50E+02	**6.02E+02**
	STD	5.37E+00	1.19E+01	6.87E+00	8.04E+00	8.63E+00	7.31E+00	7.59E+00	1.02E+01	**1.03E+00**
F7	AVG	9.29E+02	9.04E+02	1.20E+03	9.76E+02	3.04E+03	1.18E+03	1.03E+03	1.12E+03	**8.73E+02**
	STD	**3.23E+01**	5.35E+01	5.28E+01	5.24E+01	3.48E+02	3.28E+01	3.78E+01	1.01E+02	5.02E+01
F8	AVG	**8.83E+02**	9.40E+02	1.09E+03	9.36E+02	1.12E+03	1.04E+03	9.60E+02	1.00E+03	9.02E+02
	STD	3.03E+01	3.53E+01	**2.05E+01**	3.08E+01	6.35E+01	2.42E+01	3.00E+01	5.22E+01	4.53E+01
F9	AVG	**1.74E+03**	4.98E+03	6.52E+03	5.24E+03	9.93E+03	6.97E+03	4.98E+03	8.00E+03	4.01E+03
	STD	**6.74E+02**	1.38E+03	1.27E+03	1.51E+03	1.31E+03	1.01E+03	1.50E+03	2.58E+03	1.57E+03
F10	AVG	7.69E+03	4.91E+03	8.78E+03	5.17E+03	6.46E+03	7.71E+03	6.70E+03	5.98E+03	**4.16E+03**
	STD	8.12E+02	6.90E+02	**2.42E+02**	5.28E+02	1.05E+03	5.69E+02	1.67E+03	6.48E+02	5.88E+02
F11	AVG	**1.23E+03**	1.34E+03	3.09E+03	1.29E+03	3.03E+04	3.34E+03	2.76E+03	1.66E+03	1.27E+03
	STD	5.48E+01	5.97E+01	8.69E+02	**4.74E+01**	2.03E+04	5.05E+02	9.15E+02	1.99E+02	9.52E+01
F12	AVG	**1.82E+06**	2.14E+07	2.20E+09	7.07E+06	1.51E+10	4.40E+09	5.71E+08	9.57E+07	2.50E+06
	STD	**1.43E+06**	2.20E+07	5.10E+08	4.52E+06	4.74E+09	1.02E+09	4.99E+08	9.23E+07	2.13E+06
F13	AVG	**1.82E+04**	1.48E+05	8.94E+08	8.68E+04	8.29E+09	2.11E+09	1.08E+08	2.23E+05	3.45E+04
	STD	**1.43E+04**	8.84E+04	2.93E+08	5.48E+04	5.72E+09	5.98E+08	1.46E+08	2.47E+05	3.90E+04
F14	AVG	5.33E+04	5.91E+04	5.97E+05	**3.57E+04**	9.69E+06	5.71E+05	4.43E+05	1.25E+05	2.82E+05
	STD	**4.09E+04**	5.63E+04	4.90E+05	4.56E+04	1.31E+07	4.29E+05	4.84E+05	1.69E+05	2.40E+05
F15	AVG	**6.30E+03**	6.47E+04	3.93E+07	2.91E+04	3.50E+08	1.34E+06	4.93E+06	9.72E+04	7.50E+03
	STD	**6.63E+03**	5.33E+04	3.64E+07	1.35E+04	4.30E+08	1.19E+06	1.31E+07	1.48E+05	9.04E+03
F16	AVG	2.78E+03	2.94E+03	3.99E+03	2.98E+03	4.58E+03	4.59E+03	3.03E+03	3.31E+03	**2.44E+03**
	STD	5.23E+02	3.06E+02	2.28E+02	**1.77E+02**	8.69E+02	4.58E+02	3.06E+02	3.73E+02	3.42E+02
F17	AVG	**2.09E+03**	2.22E+03	2.67E+03	2.28E+03	3.82E+03	2.83E+03	2.24E+03	2.40E+03	2.26E+03
	STD	1.96E+02	2.39E+02	**1.74E+02**	2.42E+02	9.33E+02	1.98E+02	2.20E+02	1.81E+02	2.25E+02
F18	AVG	6.93E+05	1.50E+06	1.39E+07	**2.29E+05**	6.10E+07	4.95E+06	1.85E+06	1.55E+06	3.05E+06
	STD	6.73E+05	1.60E+06	1.37E+07	**1.82E+05**	5.51E+07	3.95E+06	2.31E+06	1.61E+06	3.93E+06
F19	AVG	**1.03E+04**	2.78E+06	7.24E+07	7.52E+04	6.59E+08	5.65E+06	1.90E+07	4.85E+06	2.81E+04
	STD	**1.12E+04**	1.44E+06	4.12E+07	1.12E+05	6.73E+08	3.82E+06	5.73E+07	5.24E+06	4.14E+04
F20	AVG	**2.39E+03**	2.65E+03	2.83E+03	2.64E+03	3.04E+03	2.67E+03	2.54E+03	2.63E+03	2.89E+03
	STD	**1.28E+02**	1.84E+02	1.49E+02	1.92E+02	1.71E+02	1.50E+02	2.11E+02	1.89E+02	1.77E+02
F21	AVG	**2.37E+03**	2.41E+03	2.59E+03	2.48E+03	2.67E+03	2.62E+03	2.47E+03	2.49E+03	2.38E+03
	STD	2.87E+01	7.40E+01	**2.00E+01**	4.16E+01	7.36E+01	3.71E+01	4.48E+01	4.49E+01	3.72E+01
F22	AVG	**2.30E+03**	5.05E+03	8.54E+03	4.66E+03	8.11E+03	6.12E+03	6.34E+03	6.08E+03	3.45E+03
	STD	**7.37E+00**	2.33E+03	2.41E+03	2.44E+03	9.91E+02	6.74E+02	2.57E+03	2.39E+03	1.49E+03
F23	AVG	**2.72E+03**	2.79E+03	3.07E+03	3.10E+03	3.52E+03	3.34E+03	2.90E+03	2.99E+03	**2.72E+03**
	STD	**2.15E+01**	4.92E+01	4.49E+01	1.85E+02	1.76E+02	8.30E+01	5.59E+01	9.66E+01	2.20E+01
F24	AVG	**2.89E+03**	2.93E+03	3.22E+03	3.19E+03	3.92E+03	3.59E+03	3.07E+03	3.16E+03	2.95E+03
	STD	4.70E+01	**3.23E+01**	3.49E+01	8.27E+01	2.62E+02	6.86E+01	5.82E+01	8.46E+01	5.11E+01
F25	AVG	**2.89E+03**	2.93E+03	3.42E+03	2.93E+03	9.68E+03	3.53E+03	3.17E+03	3.03E+03	**2.89E+03**
	STD	**8.57E+00**	2.79E+01	1.88E+02	2.26E+01	2.66E+03	8.51E+01	1.09E+02	6.28E+01	1.14E+01
F26	AVG	4.52E+03	4.97E+03	7.62E+03	5.93E+03	1.31E+04	8.62E+03	5.84E+03	6.76E+03	**4.41E+03**
	STD	5.31E+02	9.22E+02	3.69E+02	1.92E+03	1.51E+03	7.26E+02	5.74E+02	1.40E+03	**3.43E+02**
F27	AVG	3.24E+03	3.27E+03	3.50E+03	3.38E+03	4.58E+03	4.12E+03	3.37E+03	3.46E+03	**3.23E+03**
	STD	2.14E+01	4.28E+01	4.47E+01	1.40E+02	4.10E+02	1.69E+02	5.66E+01	1.35E+02	**1.29E+01**
F28	AVG	**3.26E+03**	3.30E+03	4.35E+03	3.27E+03	8.98E+03	4.91E+03	3.78E+03	3.46E+03	3.29E+03
	STD	3.22E+01	5.78E+01	2.96E+02	**2.14E+01**	1.20E+03	1.94E+02	2.49E+02	6.15E+01	6.74E+01
F29	AVG	**3.75E+03**	4.28E+03	5.06E+03	4.35E+03	8.62E+03	5.53E+03	4.32E+03	4.52E+03	**3.75E+03**
	STD	2.34E+02	**1.93E+02**	3.02E+02	2.32E+02	4.28E+03	3.61E+02	2.21E+02	3.86E+02	2.17E+02
F30	AVG	**1.08E+04**	9.70E+06	1.58E+08	1.17E+06	9.67E+08	1.27E+08	3.55E+07	1.13E+07	1.21E+05
	STD	**3.48E+03**	5.95E+06	5.63E+07	9.02E+05	8.95E+08	5.61E+07	2.91E+07	1.11E+07	2.53E+05
Win		/	25	30	25	29	30	29	29	20

Table 3. Comparison results of multiple algorithms when D=50

Function		MALO	SSA	SCA	PSO	BA	GA	GJO	TA	PO
F1	AVG	1.52E+07	**7.31E+03**	6.14E+10	6.50E+08	1.92E+11	6.07E+10	3.14E+10	3.40E+09	2.05E+08
	STD	8.58E+06	**7.14E+03**	7.25E+09	1.80E+09	2.59E+10	3.69E+09	6.46E+09	2.47E+09	1.53E+08
F2	AVG	**4.80E+44**	4.49E+46	2.97E+69	3.60E+45	2.65E+90	2.26E+72	8.68E+62	3.92E+63	1.79E+56
	STD	**1.24E+45**	1.68E+47	9.47E+69	1.41E+46	9.90E+90	9.39E+72	2.66E+63	1.22E+64	8.02E+56
F3	AVG	1.45E+05	1.64E+05	1.80E+05	**7.98E+04**	6.55E+05	1.47E+05	1.26E+05	1.82E+05	2.31E+05
	STD	2.21E+04	3.58E+04	2.69E+04	1.99E+04	1.75E+05	**1.24E+04**	1.88E+04	3.09E+04	1.37E+04
F4	AVG	**6.48E+02**	6.49E+02	1.16E+04	6.93E+02	6.52E+04	1.54E+04	4.98E+03	1.58E+03	6.69E+02
	STD	5.63E+01	**4.51E+01**	2.26E+03	7.52E+01	1.38E+04	1.50E+03	2.08E+03	3.96E+02	6.86E+01
F5	AVG	7.83E+02	8.48E+02	1.12E+03	8.21E+02	1.22E+03	1.06E+03	9.09E+02	1.03E+03	**7.77E+02**
	STD	1.01E+02	6.90E+01	3.92E+01	3.95E+01	5.09E+01	**3.37E+01**	5.64E+01	9.46E+01	6.97E+01
F6	AVG	**6.25E+02**	6.63E+02	6.81E+02	6.63E+02	6.84E+02	6.85E+02	6.52E+02	6.70E+02	6.33E+02
	STD	6.80E+00	1.04E+01	6.40E+00	7.23E+00	**6.39E+00**	6.76E+00	7.52E+00	8.22E+00	1.86E+01
F7	AVG	1.22E+03	1.24E+03	1.82E+03	1.39E+03	5.44E+03	1.70E+03	1.40E+03	1.68E+03	**1.12E+03**
	STD	9.72E+01	1.53E+02	7.29E+01	1.40E+02	3.65E+02	**6.97E+01**	9.14E+01	2.07E+02	7.10E+01
F8	AVG	1.06E+03	1.14E+03	1.43E+03	1.13E+03	1.51E+03	1.35E+03	1.22E+03	1.32E+03	**1.06E+03**
	STD	8.57E+01	6.79E+01	3.36E+01	**3.06E+01**	7.97E+01	3.20E+01	5.34E+01	6.96E+01	7.98E+01
F9	AVG	**9.13E+03**	1.45E+04	2.90E+04	2.10E+04	2.26E+04	2.63E+04	2.20E+04	2.82E+04	9.92E+03
	STD	4.54E+03	**2.95E+03**	3.34E+03	4.76E+03	3.24E+03	4.15E+03	6.76E+03	9.93E+03	7.43E+03
F10	AVG	1.38E+04	7.87E+03	1.51E+04	9.14E+03	1.09E+04	1.36E+04	9.88E+03	1.08E+04	**7.55E+03**
	STD	9.78E+02	9.77E+02	**3.43E+02**	8.77E+02	1.68E+03	9.31E+02	1.41E+03	8.97E+02	1.76E+03
F11	AVG	1.83E+03	1.92E+03	1.08E+04	**1.58E+03**	6.73E+04	1.27E+04	8.92E+03	3.39E+03	2.45E+03
	STD	2.34E+02	2.88E+02	2.13E+03	**7.80E+01**	2.49E+04	1.62E+03	2.98E+03	6.97E+02	6.92E+02
F12	AVG	**1.15E+07**	1.58E+08	1.97E+10	1.21E+08	9.16E+10	3.71E+10	8.86E+09	6.37E+08	6.30E+07
	STD	**1.03E+07**	9.91E+07	4.07E+09	2.15E+08	2.06E+10	4.57E+09	4.84E+09	5.63E+08	6.49E+07
F13	AVG	7.11E+03	1.86E+05	4.78E+09	7.79E+05	4.78E+10	1.55E+10	1.45E+09	4.63E+06	3.83E+04
	STD	**4.73E+03**	1.31E+05	1.28E+09	4.38E+05	1.09E+10	3.29E+09	1.60E+09	1.12E+07	1.67E+04
F14	AVG	8.10E+05	**3.49E+05**	6.39E+06	3.53E+05	9.29E+07	1.87E+07	3.28E+06	1.09E+06	1.16E+06
	STD	5.50E+05	**2.03E+05**	3.17E+06	4.26E+05	9.34E+07	8.44E+06	4.64E+06	8.66E+05	7.16E+05
F15	AVG	**7.29E+03**	8.12E+04	9.90E+08	7.73E+04	1.15E+10	9.81E+08	5.99E+08	7.40E+05	4.01E+04
	STD	**5.08E+03**	4.40E+04	3.71E+08	3.98E+04	4.96E+09	4.42E+08	1.04E+09	2.27E+06	2.35E+04
F16	AVG	**3.36E+03**	3.95E+03	6.22E+03	3.78E+03	8.88E+03	6.85E+03	4.14E+03	4.59E+03	4.02E+03
	STD	5.05E+02	4.92E+02	4.81E+02	**4.01E+02**	1.97E+03	7.24E+02	6.47E+02	7.29E+02	6.46E+02
F17	AVG	**3.32E+03**	3.52E+03	4.97E+03	3.38E+03	6.52E+04	4.24E+03	3.40E+03	3.97E+03	3.38E+03
	STD	4.71E+02	3.41E+02	3.28E+02	**2.85E+02**	6.52E+04	3.68E+02	4.50E+02	3.11E+02	4.20E+02
F18	AVG	3.10E+06	3.72E+06	3.96E+07	**1.83E+06**	2.16E+08	4.46E+07	8.24E+06	1.46E+07	9.41E+06
	STD	2.96E+06	2.40E+06	1.85E+07	**1.96E+06**	1.74E+08	1.10E+07	6.76E+06	1.09E+07	6.54E+06
F19	AVG	**1.47E+04**	6.18E+06	6.00E+08	4.90E+05	5.02E+09	3.95E+08	8.26E+07	5.35E+06	2.70E+05
	STD	**7.49E+03**	4.95E+06	2.89E+08	6.28E+05	2.79E+09	2.00E+08	1.05E+08	5.36E+06	1.07E+06
F20	AVG	3.48E+03	3.42E+03	4.23E+03	3.34E+03	4.03E+03	3.55E+03	3.63E+03	3.52E+03	**3.29E+03**
	STD	4.08E+02	3.16E+02	**2.15E+02**	2.98E+02	5.38E+02	3.74E+02	5.02E+02	3.11E+02	2.20E+02
F21	AVG	2.58E+03	2.64E+03	2.94E+03	2.71E+03	3.07E+03	3.01E+03	2.70E+03	2.81E+03	**2.57E+03**
	STD	1.08E+02	6.90E+01	**3.42E+01**	5.95E+01	1.25E+02	4.06E+01	5.48E+01	9.01E+01	8.49E+01
F22	AVG	1.50E+04	9.70E+03	1.68E+04	1.07E+04	1.22E+04	1.51E+04	1.27E+04	1.27E+04	**8.46E+03**
	STD	1.50E+03	2.08E+03	**4.49E+02**	1.03E+03	1.16E+03	8.58E+02	2.72E+03	1.34E+03	9.85E+02
F23	AVG	3.04E+03	3.05E+03	3.69E+03	3.66E+03	4.31E+03	4.25E+03	3.27E+03	3.61E+03	**3.00E+03**
	STD	1.03E+02	8.92E+01	7.49E+01	2.61E+02	2.22E+02	1.36E+02	9.25E+01	1.46E+02	**7.35E+01**
F24	AVG	**3.16E+03**	3.19E+03	3.86E+03	3.71E+03	5.09E+03	4.65E+03	3.45E+03	3.80E+03	3.24E+03
	STD	1.19E+02	7.37E+01	**7.04E+01**	1.92E+02	2.94E+02	1.70E+02	8.19E+01	1.21E+02	8.58E+01
F25	AVG	3.15E+03	3.13E+03	8.51E+03	3.15E+03	3.65E+04	8.83E+03	5.25E+03	3.73E+03	**3.11E+03**
	STD	**3.15E+01**	4.17E+01	1.09E+03	3.72E+01	5.44E+03	3.96E+02	6.33E+02	2.41E+02	3.32E+01
F26	AVG	**5.99E+03**	6.53E+03	1.31E+04	1.13E+04	2.45E+04	1.38E+04	9.44E+03	1.20E+04	6.02E+03
	STD	1.16E+03	2.98E+03	8.86E+02	2.09E+03	2.33E+03	**8.24E+02**	1.02E+03	1.51E+03	1.29E+03
F27	AVG	**3.48E+03**	3.64E+03	4.87E+03	4.26E+03	7.29E+03	6.29E+03	4.07E+03	4.49E+03	3.51E+03
	STD	9.48E+01	**9.37E+01**	2.66E+02	6.07E+02	6.99E+02	4.72E+02	1.64E+02	2.64E+02	1.24E+02
F28	AVG	3.42E+03	3.43E+03	8.26E+03	3.40E+03	1.80E+04	8.51E+03	5.72E+03	4.49E+03	**3.40E+03**
	STD	**4.59E+01**	4.81E+01	7.57E+02	6.87E+01	2.42E+03	3.86E+02	4.39E+02	3.18E+02	6.66E+01
F29	AVG	**4.19E+03**	5.73E+03	8.39E+03	5.74E+03	9.94E+04	1.34E+04	5.76E+03	6.79E+03	4.64E+03
	STD	**2.95E+02**	4.94E+02	9.98E+02	5.12E+02	1.40E+05	2.20E+03	4.00E+02	9.00E+02	3.35E+02
F30	AVG	**1.07E+06**	1.42E+08	1.15E+09	4.45E+07	7.67E+09	1.28E+09	4.11E+08	1.64E+08	4.98E+06
	STD	**2.30E+05**	3.16E+07	2.55E+08	1.50E+07	3.54E+09	3.03E+08	2.66E+08	6.23E+07	4.35E+06
Win		/	24	30	21	28	29	27	28	20

Table 4. Number of wins for the algorithms on 30 benchmark functions

Dimension	Function type	MALO	SSA	SCA	PSO	BA	GA	GJO	TA	PO	Total
D=30	Unimodal	1	1	0	1	0	0	0	0	0	3
	Multimodal	2	0	0	0	0	0	0	0	5	7
	Hybrid	7	0	0	2	0	0	0	0	1	10
	Composition	6	0	0	0	0	0	0	0	4	10
	Total	16	1	0	3	0	0	0	0	10	30
D=50	Unimodal	1	1	0	1	0	0	0	0	0	3
	Multimodal	3	0	0	0	0	0	0	0	4	7
	Hybrid	6	1	0	2	0	0	0	0	1	10
	Composition	5	0	0	0	0	0	0	0	5	10
	Total	15	2	0	3	0	0	0	0	10	30

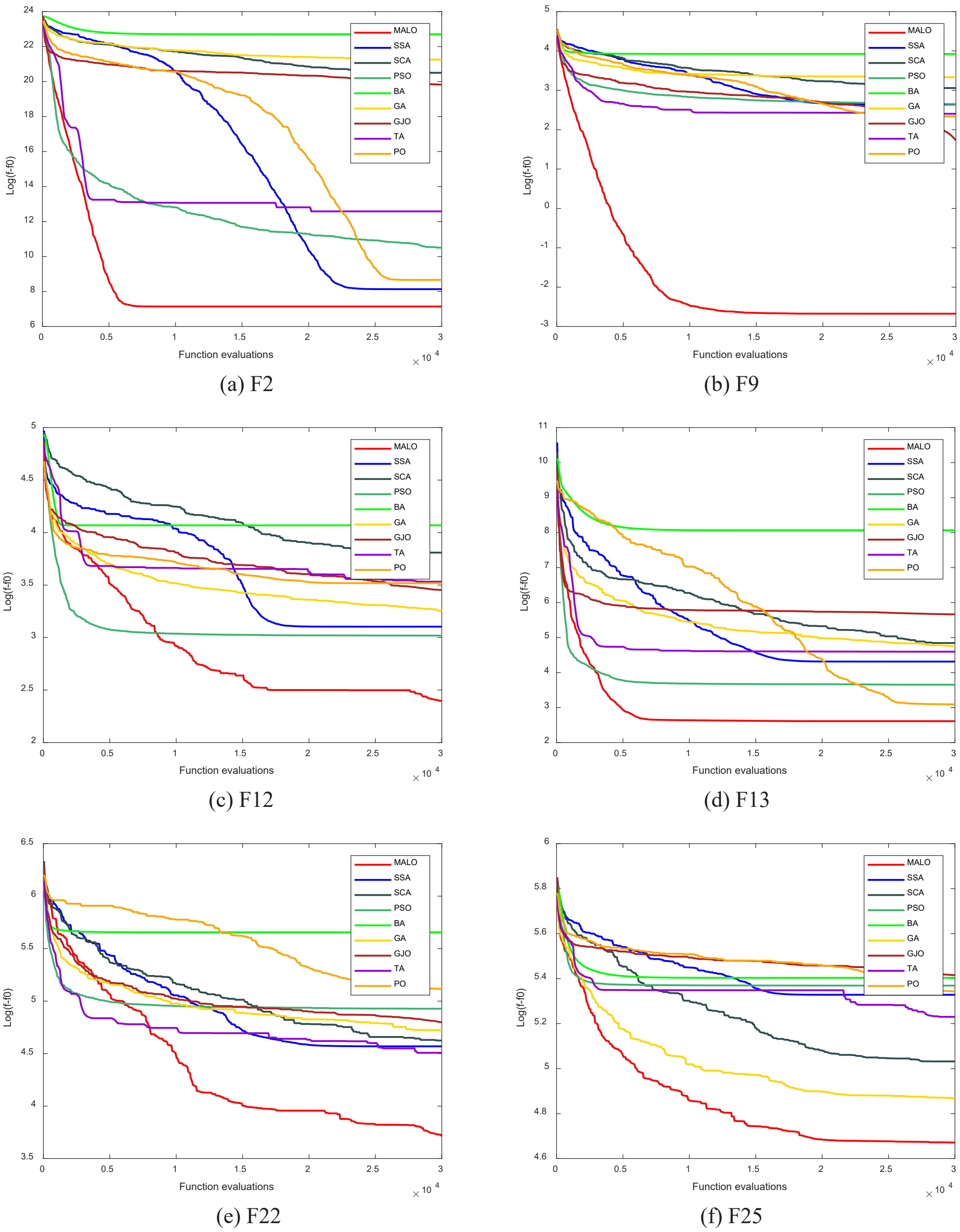


Figure 2. Convergence test results in 30 dimensions (F2, F9, F12, F13, F22, F25)

Table 3 shows that when the dimension of the solution increases to 50, MALO is also the algorithm that achieves the highest number of optimal values on the 30 benchmark functions. It achieves the optimal result on 15 functions.

In conclusion, compared with other algorithms, MALO has a significant advantage in the comparison of 30 functions. Although the performance of PO has been greatly improved on high-dimensional problems, the MALO algorithm is still slightly better than PO.

3.3 Convergence Analysis

Figure 2 shows the convergence curves of nine algorithms on six functions of F2, F9, F12, F13, F22, and F25. The six functions include one unimodal, one multimodal, two hybrid, and two composition functions. To demonstrate the convergence effect better, the y-axis is expressed as $Log\ (f - f0)$, where $f0$ represents the minimum value the benchmark function can obtain. f represents the minimum value obtained by the optimization algorithm used on the benchmark function. The x-axis is expressed as the number of evaluations of the fitness function. On the unimodal function F2, MALO converges significantly faster than other algorithms. Convergence to the optimal value only takes less than 10,000 evaluations. The same is true for the multimodal function F9, where MALO converges to the optimal value significantly better than other algorithms. On the hybrid function F12, the convergence effect of MALO is worse than PSO in the first 5000 evaluations. But the convergence of PSO stops after 5000 evaluations, and MALO continues to converge. Due to the re-practice stage of the algorithm, even if the convergence of the algorithm temporarily stagnates, MALO will continue to explore to avoid local optima. This situation is consistent with the performance of the algorithm on function F22. On the composition function F25, MALO outperforms other algorithms in the convergence effect at 3000 evaluations and has been converging continuously. After 20,000 evaluations, MALO converges to the optimal value, which has a significant advantage over other algorithms in terms of optimal value and convergence speed. In conclusion, compared with other algorithms, MALO converges to the optimal value earlier. Due to the re-practice stage, the algorithm switches the poorly performing solutions from the exploitation phase to the exploration phase to avoid getting stuck in local optima.

4 Application for Image Enhancement

In this section, the MALO algorithm is used to solve the night-time image enhancement problem. The transformation function and objective function of image enhancement are also introduced.

4.1 Gray-level Transformation Function

Gray-level transformation can increase the dynamic range of the image, expand the contrast of the image, and make it clearer. It is one of the important means of image enhancement. In this paper, the gray-level transformation function is used for image enhancement. The incomplete beta function [39] is used as a function of gray-level transformation. This transformation function is represented by the following equation.

$$T(x) = \frac{1}{\int_0^1 t^{\alpha-1}(1-t)^{\beta-1} dt} \times \int_0^x t^{\alpha-1}(1-t)^{\beta-1} dt, \quad \textbf{(15)}$$

where x is the normalized pixel intensity value. α and β are two parameters that need to be optimized. During the optimization process, the range of α and β is set to [0, 8] and [5, 10].

4.2 Fitness Function

The fitness function is used to guide the algorithm to find the optimal value. In the parameter optimization problem of image enhancement, the fitness value is closely related to the quality of the image. The fitness function proposed by AH Khan et al. [40] is used in this study.

$$fit(image) = \log(\log(SEI)) \times CE \times EI, \quad \textbf{(16)}$$

where SEI is the sum of the intensity values of edge pixels. CE represents the count of edge pixels. EI is the information entropy of the image. It reflects the average amount of information contained in the image.

4.3 Night Image Database

Nature Night-Time Image Database (NNID) is a large natural night image database established by Xiangtao et al. [41]. It is the first database to evaluate the quality of night images. The database contains 2,240 nighttime images captured in 448 different scenes. There are five images of varying brightness under the same image content. Figure 3 shows five images with different brightness under the same image content. The database also provides subjective scores of images.

Figure 3. Five images with varying brightness under the same image content

4.4 Quality Assessment of Enhanced Images

The performance of the algorithm on image enhancement is evaluated by considering the quality of the enhanced image. Since the database contains clear images with relatively high brightness, and no-reference image assessment has the disadvantage of not being able to evaluate color distortion. Therefore full-reference image assessment indicators are used in this paper, including the following two indicators.

(1) Peak Signal to Noise Ratio (PSNR). It measures the quality of the enhanced image from a statistical point of view by calculating the difference between the gray values of the corresponding pixels of the image to be evaluated and the reference image. PSNR gives the similarity measure of two images based on the mean square error (MSE) of each pixel. The higher the value of PSNR, the better the quality of the image. The calculation method of PSNR is given by the following two equations.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[I(i,j) - R(i,j)\right]^2, \quad \textbf{(17)}$$

$$PNSR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right), \quad \textbf{(18)}$$

where the size of the image is $M \times N$. MAX_I represents the maximum value of the image color, the default is 255. R represents the reference image [42].

(2) Visual Information Fidelity (VIF). It is an image quality assessment index proposed by Sheikh et al. [43] combining the natural image statistical model, image distortion model, and human visual system model. This metric treats image quality assessment as an information fidelity issue as well as explores the relationship between image information and visual quality by quantifying the loss of image information to the distortion process. Compared with PSNR indicators, VIF has higher consistency with subjective vision. The larger the value, the better the image quality.

4.5. Performance Evaluation

In this section, to verify the performance of the proposed MALO and dimensional expansion method in night image enhancement, the algorithm is compared with some image enhancement methods, including histogram equalization (HE) [44], contrast limited adaptive histogram equalization (CLAHE) [45], and PO-based image enhancement [40]. The reason for choosing the PO is that the fitness function used in this paper is consistent with it. Fourteen images with a resolution of 512×512 in the NNID database are randomly selected as evaluation images.

Table 5 and Table 6 show the PSNR and VIF values of the 14 images after enhancement with various algorithms. The best results are shown in bold. It can be seen from Table 5 that the performance of MALO is the best, with higher PSNR values on multiple evaluation images. It indicates that the image enhanced by MALO is closer to the original high-brightness image, and the effect is more natural. In terms of visualization results displayed in Figure 4 and Figure 5, the visual effect of MALO is also the best.

It can be seen from Table 6 that in the comparison of the VIF indicator, MALO is still the best performing algorithm, and CLAHE has the worst performance on VIF. And compared with the PO algorithm using the same fitness function, the proposed MALO algorithm shows better results, whether it is in the visual effect or the two quantization results of PSNR and VIF. The proposed methods MALO outperform the two traditional image enhancement methods, HE and CLAHE, in night image enhancement. These results fully demonstrate the effectiveness of the proposed MALO algorithm for image enhancement.

Table 5. The value of PSNR of 14 NNID images

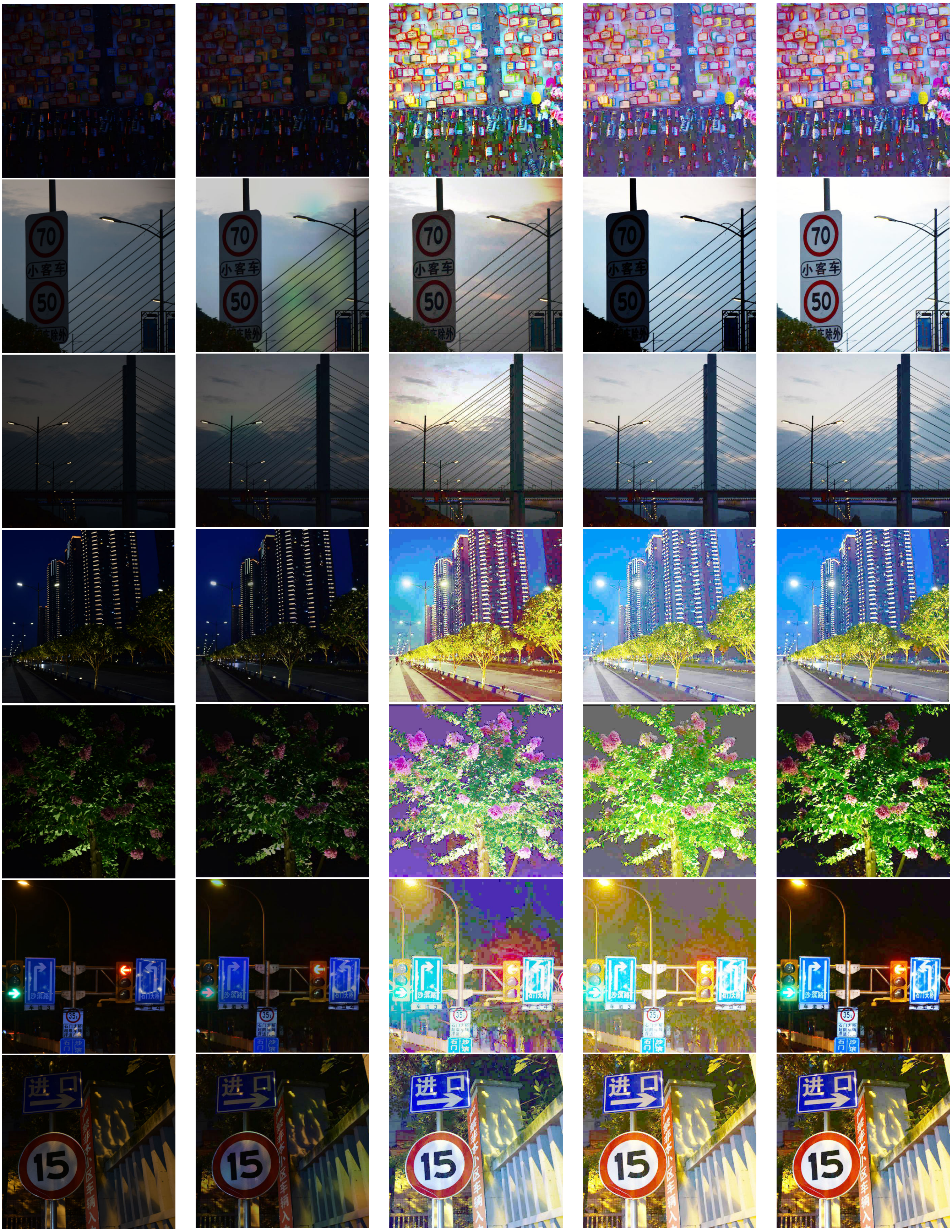
Image	MALO	PO	HE	CLAHE
Image1	**13.899**	13.254	12.365	9.012
Image2	**16.178**	13.916	12.786	10.264
Image3	**20.162**	20.024	17.471	7.763
Image4	9.745	8.437	10.322	**10.818**
Image5	**11.844**	8.452	7.492	10.923
Image6	**14.864**	8.632	8.549	12.930
Image7	**16.668**	14.321	14.107	10.195
Image8	**17.162**	16.730	13.021	7.686
Image9	**15.523**	13.722	13.642	8.374
Image10	**10.790**	10.362	9.592	8.498
Image11	**14.996**	14.990	14.863	8.063
Image12	**19.216**	15.930	16.870	9.957
Image13	**18.642**	9.790	15.783	6.287
Image14	**13.102**	12.455	9.691	5.781

Table 6. The value of VIF of 14 NNID images

Image	MALO	PO	HE	CLAHE
Image1	**0.099**	0.095	0.093	0.086
Image2	**0.156**	0.137	0.144	0.143
Image3	**0.264**	0.262	0.253	0.211
Image4	**0.058**	0.055	0.057	0.050
Image5	**0.010**	**0.010**	**0.010**	0.009
Image6	0.048	0.048	**0.049**	0.041
Image7	**0.276**	0.265	0.265	0.231
Image8	**0.125**	0.123	0.121	0.081
Image9	**0.098**	0.096	0.096	0.069
Image10	**0.065**	0.064	0.064	0.058
Image11	**0.057**	**0.057**	0.056	0.043
Image12	**0.365**	0.330	0.319	0.335
Image13	**0.123**	0.117	0.120	0.099
Image14	**0.036**	**0.036**	**0.036**	0.029

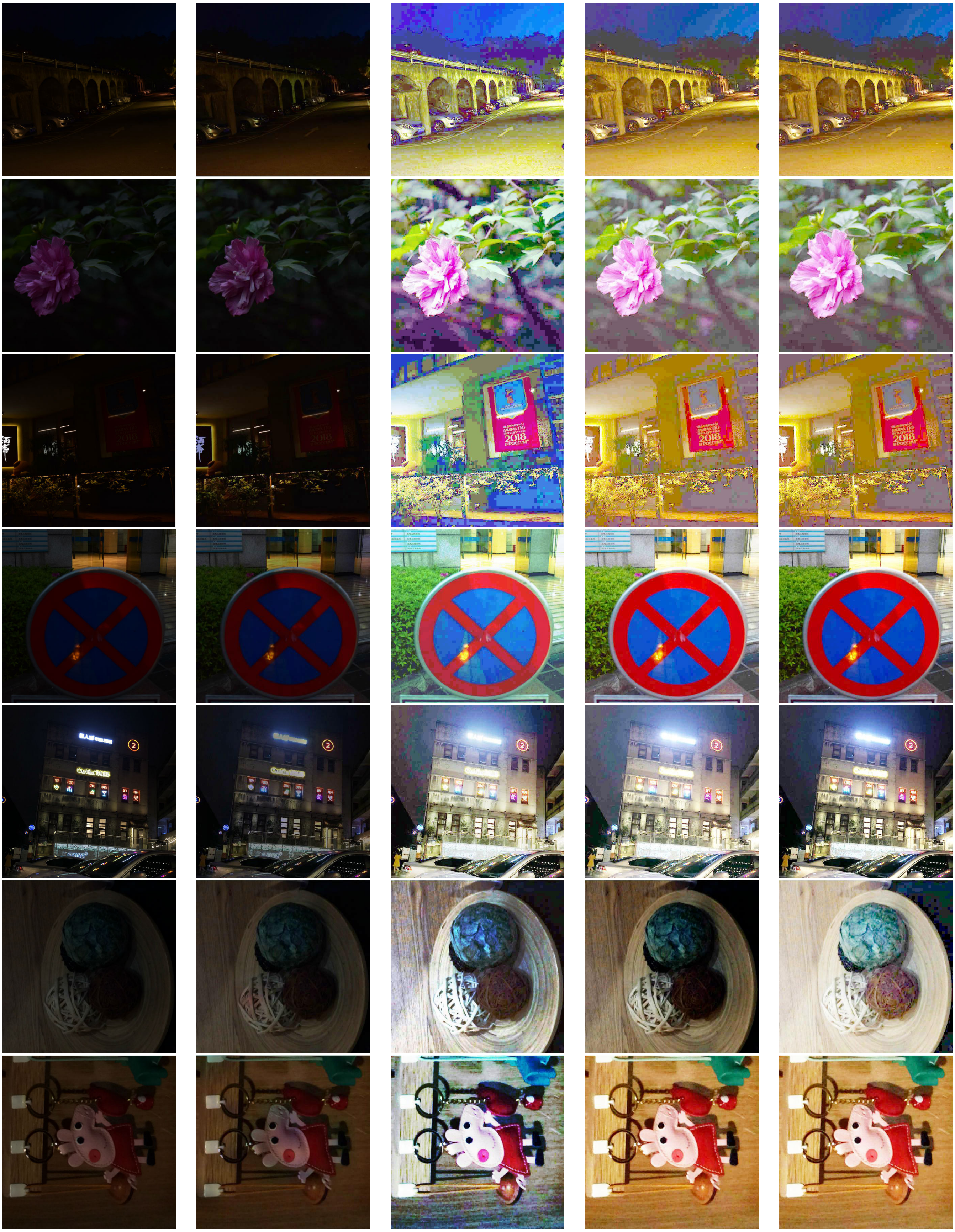
5 Conclusions and Future Perspectives

By imitating the behaviors and methods of characters learning martial arts at different stages in novels, this paper proposes a new metaheuristic algorithm for optimization. The proposed MALO algorithm uses operation bits to switch between different update strategies. According to the special plot of martial arts novel, the concept of "re-practice" is proposed, and the poorly performing solutions are brought back into the exploration stage of the metaheuristic algorithm to avoid them falling into local optimum. Experiments show that the proposed algorithm has a great advantage in performance compared with many metaheuristic algorithms. The proposed algorithm is also used to solve the problem of image brightness enhancement at night. Compared with multiple image enhancement algorithms, the proposed MALO algorithm shows superior performance. Since the proposed algorithm can only be solved in continuous space at present, it can be considered to convert it into discrete space in the following work to solve discrete problems such as path planning and workshop schedule.



(a) Original night image (b) CLAHE (c) HE (d) PO (e) Proposed MALO

Figure 4. Comparison of enhancement effects of NNID database images



(a) Original night image (b) CLAHE (c) HE (d) PO (e) Proposed MALO

Figure 5. Comparison of enhancement effects of NNID database images

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