Improved Bare Bones Particle Swarm Optimization based on Cauchy Distribution and its Application in Spectral Reconstruction

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***Abstract*—In view of the shortcomings that particle swarm optimization is easy to fall into local optima and difficult to solve complex problems, the combination of Gaussian distribution and Cauchy distribution was used in the position updating formula to improve the particle diversity, and Cauchy perturbation was added to the swarm optimal position to further improve its global searching ability. In the experiment, ten benchmark test functions were used to test two proposed modifications in the study, and compared with the four classical particle swarm algorithms, the results show that the proposed algorithm had high solving accuracy and good solving stability, especially in solving complex functions. The proposed algorithm was utilized in spectral reconstruction based on wideband multi-illuminant imaging. The experimental results confirm that comparing with the classical PSO algorithm, the proposed algorithm is good at searching for global optimum especially for complicated engineering problems.**

Keywords—particle swarm optimization, bare bones particle swarm optimization, swarm intelligence, Cauchy distribution, Cauchy perturbation, spectral reconstruction

I. Introduction

With the development of science and technology and the advancement of computer technology, now the society has entered the era of big data, there are a large number of problems with higher dimensions, geometric growth of data, stronger parameter coupling and other characteristics. In addition, optimization problems are also widely occurring in electrical, communications, machinery, economy, finance and other fields, as long as decision-making is needed, there will be optimization problems. In order to adapt to the rapid development of society and efficiently solve more complex problems, following bionics, researchers once again learned from nature, resulting in the birth of swarm intelligence algorithms. For example, several classical swarm intelligence algorithms such as particle swarm algorithm inspired by bird flock foraging, cultural algorithm encouraged according to human social and cultural evolution model, artificial fish swarm algorithm generated according to the living habits of fish groups, and ant colony algorithm inspired by ant colony foraging. Among them, Particle Swarm Optimization (PSO) is one of the widely studied swarm intelligence algorithms, based on Reynolds [1] and Heppner et al. [2] analysis model of bird flock flight behavior, Kennedy and Eberhart [3] formally proposed the PSO algorithm in 1995.

Since the PSO algorithm has the advantages of concise algorithm and simple theoretical structure, there are a large number of studies for improving PSO. Shi et al. [4] proposed that the inertia-weighted PSO, generally named as Standard PSO (SPSO). In consideration of the shortcomings of SPSO such as easy premature convergence and low optimization accuracy, scholars improved its parameters and the population topology. In many SPSO improvement studies, there are some widely known methods, such as FIPS (Fully Informed Particle Swarm) [5], in which particle updates do not only use the optimal particles in their neighborhood, but also use the historically optimal weighted average of all members in the neighborhood to guide updates. As SPSO improvements become more sophisticated, it become harder and harder to improve the way particles operated, until in 2003, Kennedy, the inventor of PSO, proposed a clearer form of particle swarm algorithm: Bare-bones PSO (BBPSO) [6], and to use Gaussian distribution to control particle evolution.

BBPSO is a more concise particle swarm algorithm, in which the velocity attribute of particles is removed in evolution, and evolution is completed in the form of random distribution. BBPSO's simple cooperative probabilistic searching method can improve the searching efficiency and accuracy of the algorithm, and avoid the complex parameter setting of SPSO, which is

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more widely used. Therefore, the algorithm improvement, analysis and application of BBPSO have always been a hot spot in the field of particle swarm studies, such as Sun et al. proposed quantum-behaved particle swarm operation (QPSO) [7], and Coelho proposed Gaussian quantum particle swarm algorithm [8]. Compared with the classical particle swarm algorithm, the biggest difference between BBPSO and the classical particle swarm algorithm is that the next movement position of the particle does not depend on the current particle position, but on the current historical optimal position of the particle.

The improvement of particle swarm optimization essentially revolves around two goals: first, to solve the problem that the algorithm is prone to premature convergence, so that the algorithm has better global exploration ability; The second is to improve the searching accuracy of the algorithm in the neighborhood, so that the algorithm has better local development capabilities. The greater the diversity of the particle swarm and the higher the degree of dispersion, the less likely the particles are falling into the local optimal solution, and the better global exploration capabilities the algorithm has. The more concentrated the particle swarm, the more search accurate the particles in the current neighborhood, and the better the local development ability of the algorithm. However, particle diversity is not always as high as possible. If the particle diversity is always maintained at a high level, it may cause the algorithm not be able to converge. Therefore, the ideal situation is to maintain a certain high diversity of particles at the beginning of iteration, and rapidly reduce the diversity when approaching the region where the global optimal solution is located, so that the swarm converges to the global optimal solution.

In order to solve the above problems, the introduction of mutation mechanism in population evolution is the most widely studied method, which can effectively improve the problem of premature convergence and improve the optimization efficiency, and its mechanism of action is to force particles to leave their current position to achieve the purpose of regulating particle diversity. The mutation mechanism was first seen in Van Den Bergh's Multi-start PSO (MPSO) [9], which reinitializes the particle position after a certain number of iterations; Krohling and Mendel [10] generate perturbations through Gaussian distribution or Cauchy distribution to help the population jump out of the local optimal, but different test functions need to set different perturbation amplitudes; Blackwell and Majid [11-12] propose two types of BBPSO with uniform variation (BBPSO with Jumps, BBJ): BBJ1 and BBJ2, both algorithms slow down the loss of population diversity by setting the probability so that particles can perturb according to a uniform distribution of mutation points, but too much variation will affect efficiency, and too little is not conducive to group jumping out of the local optimum; Campos et al. [13] use the heavy-tailed distribution instead of the Gaussian distribution to produce new positions of particles, thereby increasing the chance of the algorithm jumping out of local extremes, called SMA-BB (BBPSO with Scale Matrix Adaptation).

The particle updating mechanism in BBPSO has intuitive physical significance, can easily adjust the searching scope of particle. The modifications based on BBPSO in this study lies in two aspects, one is to set the possible distribution position of particles in 50% probability to present two random distributions, namely Cauchy distribution and Gaussian distribution, adding Cauchy distribution is conducive to the diversity of particles, making it easier to jump out of the local optimal solution; The second is to update the global optimal position of group by adding a Cauchy perturbation to search for a better solution around the global optimal position.

II. IMPROVED BBPSO ALGORITHM

In classical particle swarm algorithm, particle *i* will converge to a point between the historical best and the neighborhood best. Inspired by this, Kennedy's original BBPSO form is shown in Equation (1):

$$x_i^{k+1} = \begin{cases} N\left(\left(pBest_i^k + gBest^k\right)/2, \left|pBest_i^k - gBest^k\right|\right) & r < 0.5 \\ pBest_i^k & r \geq 0.5 \end{cases} \quad (1)$$

where, $N\left(\left(pBest_i^k + gBest^k\right)/2, \left|pBest_i^k - gBest^k\right|\right)$ is a Gaussian distribution with the mean of $\left(pBest_i^k + gBest^k\right)/2$, the standard deviation of $\left|pBest_i^k - gBest^k\right|$, the new position x_i^{k+1} is a Gaussian sampling point near the midpoint of the local optimal and global optimal positions, and the $pBest_i^k$ represents the local optimal position of particle *i* in the *k*th iteration. $gBest^k$ indicates the global optimal position in the *k*th iteration.

The BBPSO algorithm utilizes the expectation and standard deviation of the Gaussian distribution to provide an efficient searching domain for particles. As the iteration progresses, the searching domain will gradually decrease, which will lead to the effective searching range being too concentrated, and it is difficult for the algorithm to obtain the optimal solution with high accuracy.

In order to increase the diversity of particles, improve the local exploration ability of the algorithm, and make it easier to jump out of the local optimal, it is proposed to update the particle position in BBPSO by combining Gaussian distribution and Cauchy distribution, as shown in Equation (2):

$$x_i^{k+1} = \begin{cases} N\left(p * pBest_i^k + (1-p) * gBest^k, \left|pBest_i^k - gBest^k\right|\right) & r < 0.5 \\ \left(p * pBest_i^k + (1-p) * gBest^k\right) * \left(1 + rand * C(0,1)\right) & r \geq 0.5 \end{cases}, \quad (2)$$

where *p* and *r* represent uniformly distributed random number in the range of [0,1], $N\left(p * pBest_i^k + (1-p) * gBest^k, \left|pBest_i^k - gBest^k\right|\right)$ represents the Gaussian distribution similar to that used in BBPSO, *C*(0,1) represents a random number generated by Cauchy distribution with a scale parameter 1 centered at the origin, and here *C*(*α*, *β*) is calculated as shown in Equation (3):

$$C(\alpha, \beta) = \alpha - \frac{\beta}{tan(p\pi)} = \alpha + \beta tan\left((p-0.5)\pi\right), \quad (3)$$

where *p* is a uniformly distributed random number in the range of [0,1].

In addition, in order to further improve the global exploration capability of the algorithm, Cauchy perturbation is added to update the global best position, as shown in Equation (4):

$$gBest' = gBest^k * \left(1 + rand * C(0,1)\right). \quad (4)$$

Cauchy perturbation is used to make the particle explore again around the overall optimal position, updating the global optimal solution if it finds a better solution than the current one, and maintaining the original particle optimal position if it is not found. The pseudo-code for the proposed algorithm is listed as follows:

Algorithm 1: proposed algorithm based on BBPSO

```
Initialize population;
for k = 1 to maximum iteration do
    Update particles positions by Equation (2);
    Compute fitness f(x);
    Update the pBest_i^k and gBest^k;
    Cauchy perturbation by Equation (4);
    if f(gBest')<f(gBest^k) then
            gBest^k = gBest';
    end if
end for k
```

III. Analysis and Discussion

A. Test functions and algorithms for comparison

For analysis and comparison of algorithms, scholars have put forward some well-studied benchmark problems, such as Rosenbrock, Ackley, Griewank and other functions. [14] Even so, different researchers have different settings for function dimensions, rotation angles, etc., and some algorithms have advantages for multimodal problems, while others are more suitable for unimodal problems. Therefore, in order to study the algorithm more comprehensive, ten test functions were selected in this study, including Sphere, Rosenbrock, Schwefel 1.2, Schwefel 2.21, Schwefel 2.22, Quartic, Rastrigin, Griewank, Ackley, and Levy, as shown in Equation (5)-(14).

Sphere $$f(x) = \sum_{i=1}^{n} x_i^2 \quad (5)$$

Rosenbrock $$f(x) = \sum_{i=1}^{n-1}[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2] \quad (6)$$

Schwefel 1.2 $$f(x) = \sum_{i=1}^{n}(\sum_{j=1}^{i} x_j)^2 \quad (7)$$

Schwefel 2.21 $$f(x) = max_i \{|x_i|, 1 \le i \le n\} \quad (8)$$

Schwefel 2.22 $$f(x) = \sum_{i=1}^{n}|x_i| + \prod_{i=1}^{n}|x_i| \quad (9)$$

Quartic $$f(x) = \sum_{i=1}^{n} i x_i^4 + random[0,1) \quad (10)$$

Rastrigin $$f(x) = \sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i) + 10] \quad (11)$$

Ackley $$f(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n} cos2\pi x_i\right) + 20 + c \quad (12)$$

Griewank $$f(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \quad (13)$$

Levy $$f(x) = sin^2(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2\left(1 + 10sin^2(\pi y_1 + 1)\right) + (y_n - 1)^2(1 + sin^2(2\pi y_n)) \quad (14)$$
$$y_i = 1 + \frac{x_i - 1}{4}$$

The searching range, dimension, optimal solutions, and fitness of expressions are shown in Table I. Among them, the first six test functions are unimodal, and the last four test functions are multimodal.

The four classical PSO algorithms SPSO, BBPSO, FIPSO and QPSO were selected for comparison in the study. In order to test the performances of two proposed modifications in this paper: updating positions by combining Gaussian distribution and Cauchy distribution, and Cauchy perturbation, the algorithm of BBPSO plus combining random distributions (named as GCBBPSO1), the algorithm of BBPSO plus Cauchy perturbation (named as BBPSO+C), and the full proposed algorithm (named as GCBBPSO) were compared. Table II describes the parameter settings of the above seven algorithms.

TABLE I. Information of ten test functions

Function	Search range	Dimension	x_{min}	Fitness
Sphere	[-100,100]	30	0	0
Rosenbrock	[-2.048,2.048]	30	1	0
Schwefel 1.2	[-100,100]	30	0	0
Schwefel 2.21	[-100,100]	30	0	0
Schwefel 2.22	[-10,10]	30	0	0
Quartic	[-1.28,1.28]	30	0	0
Rastrigin	[-5.12,5.12]	30	0	0
Ackley	[-32,32]	30	0	0
Griewank	[-600,600]	30	0	0
Levy	[-10,10]	30	1	0

TABLE II. Algorithm parameter settings

Algorithm	Parameter settings
PSO	w=0.7298，c_1=c_2=2.05
BBPSO	Random structure
FIPSO	w=0.7298；c=0.5984；Von Neumann Topology
QPSO	c_1=1.7，c_2=1.8
GCBBPSO1	Random structure
BBPSO+C	Random structure
GCBBPSO	Random structure

B. Results and discussion

For all algorithms, the number of particles was 50, the maximum number of iterations was 50,000. The mean and standard deviation of the optimal value, after running 100 times independently for each test functions, were calculated and are listed in Table III-IV, and the convergence curves of ten benchmark functions for seven algorithms are shown in Fig. 1. In Table III-IV, the values marked in bold font are the best performed algorithm for each function. In Fig. 1, each function was plotted in two forms: fitness (or cost function) against iteration, and log10 of fitness against iteration.

For the ten benchmark functions, it can be seen from Table III and IV that the three proposed algorithms, GCBBPSO1, BBPSO+C, GCBBPSO based on BBPSO performed better than that of SPSO, BBPSO, FIPSO and QPSO in terms of solving accuracy and stability. It confirms that the two modifications in the proposed algorithm significantly improved the solving ability for different types of optimized problems.

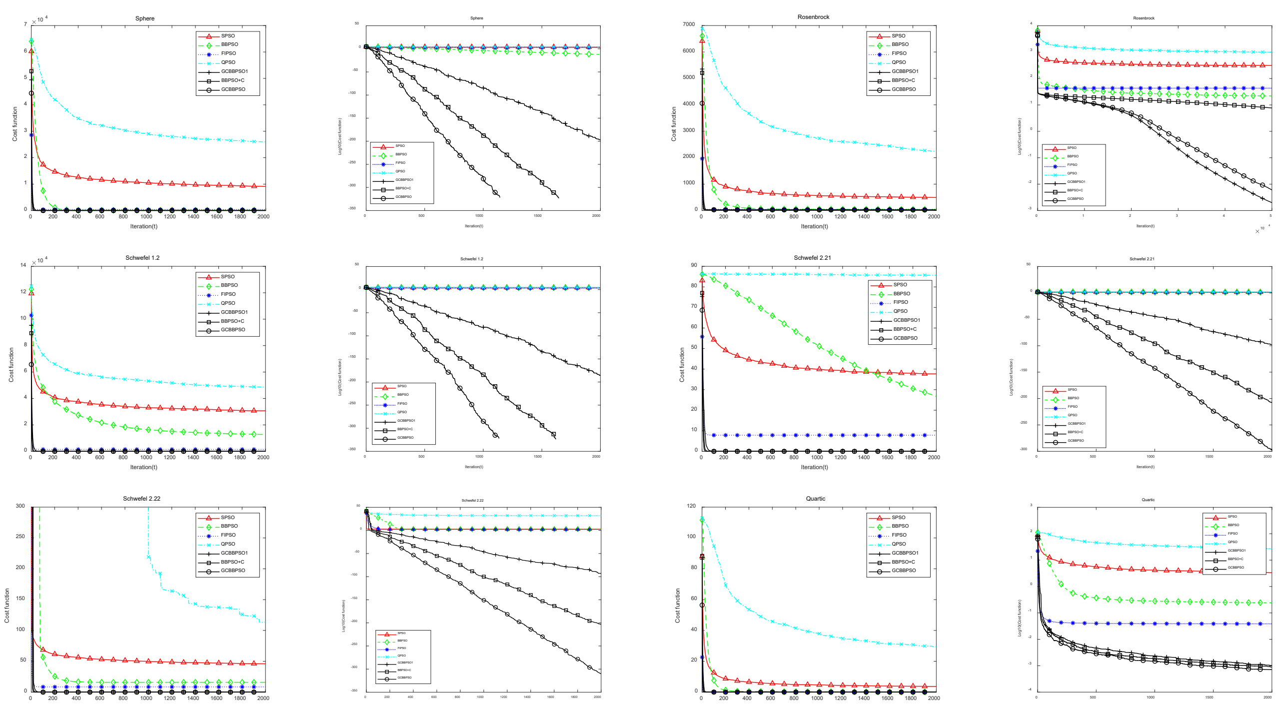
It can be seen from Fig. 1 that the three convergence curves for the proposed algorithm were always below that of four classical PSO algorithms, it means the proposed algorithm can solve the problems more efficiently than that of classical PSO methods, e.g., for most functions except Rosenbrock, the proposed methods can obtain the correct results within 500 iterations. It can be seen that the phenomena of premature convergence more or less exist for four classical PSO algorithms. Comparing the convergences between three versions of the proposed algorithm, GCBBPSO can converge on the optimal solutions more quickly than that of others except for two functions, Rosenbrock and Levy.

TABLE III. THE MEAN OF THE OPTIMAL VALUES FOR THE SEVEN ALGORITHMS

	SPSO	BBPSO	FIPSO	QPSO	GCBBPSO1	BBPSO+C	GCBBPSO
Sphere	-2.01E-01	-2.93E-164	-2.33E-02	3.38E-01	8.29E-165	1.31E-164	**-5.34E-165**
Rosenbrock	1.16E-01	9.15E-01	2.26E-02	2.29E-01	**9.95E-01**	6.77E-01	9.94E-01
Schwefel 1.2	5.23E-02	5.00E-02	2.76E-02	9.25E-03	5.75E-166	4.83E-165	**3.67E-165**
Schwefel 2.21	4.01E-02	9.11E-15	1.22E-01	2.74E-01	**0.00E+00**	**0.00E+00**	**0.00E+00**
Schwefel 2.22	7.79E-01	-1.60E+00	1.14E-02	1.10E+00	**0.00E+00**	**0.00E+00**	**0.00E+00**
Quartic	-4.60E-04	-7.15E-04	6.33E-04	2.27E-03	-1.51E-04	**-4.21E-05**	1.10E-04
Rastrigin	8.42E-03	3.35E-02	1.48E-02	4.93E-03	**5.57E-11**	8.33E-11	-1.08E-10
Ackley	1.88E-01	1.12E-02	1.37E-02	-2.33E-01	2.49E-18	**-1.06E-18**	-4.97E-18
Griewank	-4.73E-01	2.03E-01	-3.78E-01	-4.91E+00	**-2.68E-11**	-3.77E-10	9.42E-11
Levy	3.51E+00	1.24E+00	-1.93E-02	-3.11E+00	8.40E-01	**9.99E-01**	8.46E-01

TABLE IV. COMPARISON OF THE STANDARD DEVATION OF THE OPTIMAL VALUES FOR THE SEVEN ALGORITHMS

	SPSO	BBPSO	FIPSO	QPSO	GCBBPSO1	BBPSO+C	GCBBPSO
Sphere	1.02E+00	**0.00E+00**	3.38E-01	1.74E+00	**0.00E+00**	**0.00E+00**	**0.00E+00**
Rosenbrock	9.03E-02	2.20E-01	3.09E-02	6.89E-02	**8.21E-03**	1.12E-01	9.77E-03
Schwefel 1.2	3.94E+00	4.57E+00	8.70E-01	3.61E+00	**0.00E+00**	**0.00E+00**	**0.00E+00**
Schwefel 2.21	9.19E-01	9.17E-14	2.50E-01	2.22E+00	**0.00E+00**	**0.00E+00**	**0.00E+00**
Schwefel 2.22	3.37E+00	5.08E+00	9.22E-01	4.01E+00	**0.00E+00**	**0.00E+00**	**0.00E+00**
Quartic	5.89E-02	4.55E-02	2.11E-02	9.56E-02	2.29E-03	**1.51E-03**	1.52E-03
Rastrigin	1.70E-01	1.36E-01	5.24E-02	1.41E-01	**3.26E-10**	4.76E-10	3.74E-10
Ackley	5.01E-01	7.29E-01	9.07E-02	5.75E-01	2.78E-17	**1.72E-17**	2.35E-17
Griewank	6.11E+00	1.09E+01	1.48E+00	9.76E+00	**2.26E-09**	3.69E-09	2.90E-09
Levy	2.00E+01	4.59E+01	4.66E+00	2.02E+01	1.07E-01	**2.77E-02**	1.04E-01



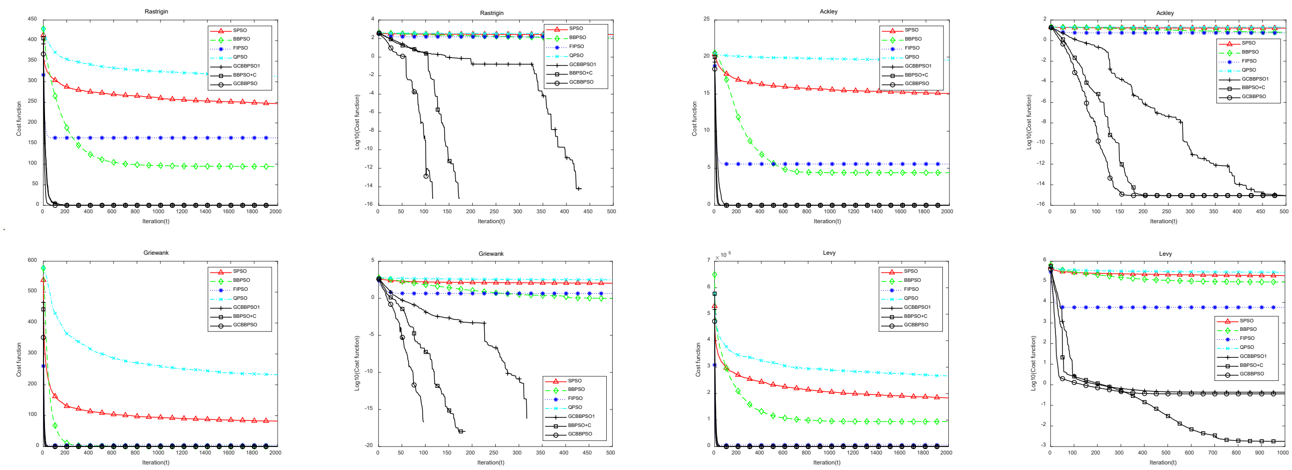


Fig. 1. Convergence curves of ten benchmark functions for seven algorithms

C. Applications in spectral reconstruction

PSO algorithm has been widely used in various fields [15-18]. In color science, spectral reflectance is the essential optical attribute of an object. Spectral reflectance reconstruction based on camera responses provides an effective way for color measurement. The workflow for spectral reconstruction based on multi-illuminant imaging is shown in Fig. 2, where spectral estimation matrix is usually trained by an optimization algorithm based on camera responses and measured reflectance of training samples.

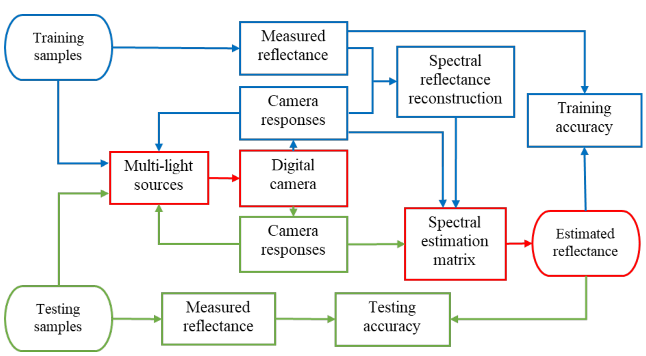


Fig. 2. The workflow for spectral reconstruction based on multi-illuminant imaging

The optimized problem in matrix form can be descripted in Equation (15)

$$\hat{\boldsymbol{R}} = \boldsymbol{GV}, \tag{15}$$

where $\boldsymbol{V}$ is a $\boldsymbol{C}\times\boldsymbol{M}$ matrix of camera responses, $\hat{\boldsymbol{R}}$ is a $\boldsymbol{N}\times\boldsymbol{M}$ matrix of estimated reflectance, $\boldsymbol{G}$ is a $\boldsymbol{N}\times\boldsymbol{C}$ spectral estimation matrix; $\boldsymbol{M}$ is number of samples, $\boldsymbol{N}$ is number of spectral bands, typically $\boldsymbol{N}$=31 for spectral wavelength from 400 to 700nm with 10 nm intervals, $\boldsymbol{C}$ is the number of camera channels. In a multi-illuminant imaging system, images are token using a color camera under multiply light sources, thus the number of camera channel $\boldsymbol{C}$ is depended on the number of light sources used. If the images are taken over one light source, $\boldsymbol{C}$ = 3; if the images are captured in sequence over two different light sources, $\boldsymbol{C}$ = 6, and so on. The larger the camera channel C is, the more complicate the optimized problem will be.

To solve the Equation (15), it is common to use an optimization algorithm, such as pseudo-inverse, and Wiener estimation [19], etc., to minimize the root mean square error (RMSE) between the estimated reflectance $\hat{\boldsymbol{R}}$ and measured reflectance $\boldsymbol{R}$ of training samples. Unfortunately, the traditional estimation algorithm may obtain a matrix $\boldsymbol{G}$ at a local optimal solution if the optimized problem is too complicated, thus a global optimization algorithm based on particle swarm optimization (PSO) was proposed for spectral reconstruction in the current study.

In the experiment, two color charts, a ScoColor textile color chart (ST240) from Zhejiang Scocie Instrument, China, and a ColorChecker Digital chart (SG140) from X-Rite, as shown in Fig. 3, were used as training samples and testing samples, respectively. The reflectance of each color in two charts was measured using a spectrophotometer Ci64UV and served as the target data of the experiment.

The experiment was carried out under an enclosed environment with nine program-controlled light sources, such as HZ, A, D50, D65, D75, D90, D100, D120 and D160, etc. Images of two color charts under different light sources were captured in sequence using a color industrial camera with a resolution of 4096×3000 and a depth of 12 bits, and camera responses for colors in two charts were extracted from those images, and used as the original experimental data for the current study.

For comparison, the spectral estimation matrix $\boldsymbol{G}$ was estimated using four algorithms including traditional pseudo-inverse (PI), SPSO, BBPSO, and the proposed GCBBPSO. The pseudo-code for spectral reconstruction utilizing a PSO algorithm is listed as follows:

Algorithm 2: spectral reconstruction using a PSO

1 for i = 1 to 31 (for wavelength from 400 to 700nm) do
2 Run a PSO, e.g., SPSO, BBPSO or GCBBPSO;
3 $G(i, :) = gBest^k$;
4 end for i

In order to investigate the optimal number and combination of light sources in multi-illuminant imaging, the experiments of spectral reconstruction were conducted from images under different illuminant combinations, i.e., all possible combinations from one to five light sources. Due to the limitation of space, only the average testing accuracies in terms of CIEDE2000 color difference ΔE_{00} [20] under different light source combinations are listed in Table V. The values marked in bold font in Table V are the best illuminant combination for each algorithm. The smaller the ΔE_{00} value, the higher the accuracy of color predicted.

(a) (b)

Fig. 3. Two sets of samples (a) ST240, (b) SG140, used in the experiment

TABLE V. AVERAGE TESTING ACCURACY OF SG140 IN TERMS OF ΔE_{00} UNDER DIFFERENT ILLUMINANT COMBINATIONS

Light sources	**PI**	**SPSO**	**BBPSO**	**GCBBPSO**
Single	2.61	2.61	**2.61**	2.61
Two	**1.24**	**1.35**	6.43	**1.24**
Three	1.39	3.68	11.23	1.31
Four	1.74	5.05	12.13	1.43
Five	2.07	6.00	11.79	1.64

It can be seen from Table V that for reconstructing spectral from images under single illuminant, the four tested algorithms were working well and performed almost similarly, that means they can solve the simple optimized problems. However, the SPSO and BBPSO did not work with increasing the complexity of the problems, e.g., BBPSO and SPSO did not work after two- and three-illuminant combinations, respectively. The proposed GCBBPSO can find the optimal solutions for all tested cases. Comparing with PI method, the proposed method can obtain more accurate results for more complicated optimized problems. It is concluded that comparing with the classical SPSO and BBPSO algorithm, the proposed GCBBPSO algorithm is good at searching for global optimum for complicated problems.

IV. CONCLUSION

Aiming at the defects that particle swarm optimization is easy to fall into local optimum, a combination of Gaussian distribution and Cauchy distribution was used to update the particles positions, which can make it easier for particles to jump out of local optimum and make the algorithm better to cover the space of the solution. After updating the best position of all particles, Cauchy perturbation was used to further search around the current best particle position, which improves the global searching ability of particles. The proposed algorithm was tested using ten benchmark functions and an engineering optimized problem. The experimental results verify the effectiveness of the proposed algorithm.

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