An Extension of Bamboo Forest Growth Optimization Algorithm

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***Abstract*—The Bamboo Forest Growth Optimization Algorithm (BFGO) is an innovative and flexible meta-heuristic optimization algorithm inspired by the growth pattern of bamboo forests, which first establish roots and extend before growing freely. This algorithm has achieved good results in solving optimization and engineering problems. However, it suffers from insufficient global exploration capabilities and is prone to getting stuck in local optima. Drawing on additional growth characteristics of bamboo forests, this paper extends BFGO's search strategy, reconstructs the bamboo growth model, and designs an elimination strategy to select elite individuals. Comparative testing against several classical meta-heuristic algorithms and their improved variants on the CEC2017 and CEC2013 test set. The results demonstrate that the extended BFGO algorithm achieve the best performance, fully demonstrates the effectiveness and competitiveness of the improved strategy.**

***Index Terms*—Bamboo forest growth optimization algorithm, Swarm intelligence algorithm, Logistic growth model, Natural selection strategy**

I. Introduction

In recent years, research and applications related to meta-heuristic algorithms [1]–[5] have developed rapidly [6] and are widely used in various optimization problems [7], [8]. These algorithms are inspired by some real-life phenomena or laws so as to obtain an approximate optimal solution to the problem by iterative search within a given problem horizon. Compared with the traditional mathematical methods which are limited by strong constraints such as the differentiability and continuity of the objective function, these algorithms can continuously search in non-convex, high-dimensional, or discrete-continuous solution spaces by defining the fitness function, and have the advantages of weak dependence on the problem domain, high adaptability, scalability and robustness to complex constraints, and thus they can deal with a wide range of large-scale and complex problems. On the other hand, bamboo forest growth optimization algorithms are inspired by the physiological properties and growth process of bamboo [9]. Bamboos, as herbaceous plants, can grow to the height of trees, which is highly related to their unique growth pattern [10], [11]. The "slow-fast-slow" growth cycle of bamboos and their rapid stem elongation contribute to their ecological dominance: bamboos first use their root system to grow and spread in random directions over several kilometers above the ground in order to continuously absorb nutrients from the soil for optimal growth. Bamboo shoots emerging from the soil can grow very long in a short period of time. Therefore, Feng et al. [9] mathematically modeled the two phases of complete extension of bamboo whips and rapid growth of bamboo and mapped these two growth processes in an optimization algorithm. In the bamboo whip extension stage, individuals on each population move in different directions to facilitate global exploration of the solution space; in the bamboo growth stage, each individual is locally exploited according to the constructed growth model so as to update the position. This is the overall framework of the bamboo forest growth optimization algorithm.

The BFGO algorithm is different from the classical meta-heuristic algorithm, it is inspired by this special growth law of

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bamboo, and carries out global exploration and local search in stages, which is innovative and performs well in the practice of optimization problems with other algorithms for engineering applications, which shows that it is quite competitive in dealing with complex problems, but its performance on the CEC2017 test set [12] shows that that its Exploration and development capabilities still needs to be improved.

This paper proposes an extended bamboo forest growth optimization algorithm (E-BFGO), which aims to address the limitations of BFGO. In the natural growth process of bamboo forests, in addition to the unique growth characteristics of bamboo forests themselves and the iterative law, it will be accompanied by light, water, soil nutrients and other external environmental factors that affect growth. Bamboo has a well-developed root system, which is concentrated underground to form a dense root network in the early stage. If the soil is in deep and loose fertile sandy loam or light loam, it can better satisfy the demand of its root system growth. After the bamboo whip absorbs nutrients in the soil for months or even years to form shoots, the bamboo shoots rely on light and store nutrients to grow rapidly, produce branches and leaves, and wait until the new shoots of the bamboo whip regenerate to complete the population iteration. This paper draws inspiration from this and adds and improves more strategies based on the original algorithm. In BFGO, the study on bamboo growth is not comprehensive enough. Accordingly, The original growth scheme in the expansion scheme is replaced and improved, with more growth factors being considered and incorporated into the bamboo growth process. The algorithm structure of BFGO is constructed and improved in accordance with the ecology of bamboo forests in reality. The new strategy designs local search methods in the whip extension stage and bamboo growth stage to complement the natural replacement mechanism of the population, which greatly helps the original algorithm to go beyond the local optimal solution and significantly improves the global exploration capability.

II. BFGO

This section will detail the Bamboo Forest optimization algorithm, the inspiration for the expansion strategy, and their mathematical models.

The core of the BFGO algorithm lies in referencing the common growth habits of bamboo plants, including the exploration of underground stem extension and rapid growth of above ground parts, and then analyzing its mathematical model to transform it into a search strategy in the algorithm, with two distinct phases: breadth exploration and local search.

During the bamboo whip extension stage, the individuals of each cluster move in the main direction with three benchmarks for breadth exploration: the group cognitive term, the group memory term and the group center term. The specific movement equations are shown as:

$$X_{t+1} = \begin{cases} X_G + Q \times (\sigma \times X_G - X_t) \times cos\alpha, & r_1 < 0.4 \\ X_P(k) + Q \times (\sigma \times X_P(k) - X_t) \times cos\beta, & 0.4 \leq r_1 < 0.7 \\ C(k) + Q \times (\sigma \times C(k) - X_t) \times cos\gamma, & else \end{cases} \tag{1}$$

$$cos\alpha = \frac{X_t \cdot X_G}{|X_t| \times |X_G|} \tag{2}$$

$$cos\beta = \frac{X_t \cdot X_P(k)}{|X_t| \times |X_G|} \tag{3}$$

$$cos\gamma = \frac{X_t \cdot C(k)}{|X_t| \times |X_G|} \tag{4}$$

$$Q = 2 - \frac{t}{T} \tag{5}$$

Where X_G represents the individual with the best fitness among all individuals, $X_P(k)$ represents the individual with the best fitness within the k-th bamboo whip cluster, and $C(k)$ represents the central position of the k-th bamboo whip cluster, typically calculated as the average of the positions of all individuals within the cluster. α, β, and γ denote the three extension directions of the rhizome system, namely, the direction of the current individual moving towards the global optimal solution, the population optimal solution, and the center of the population. In addition, σ is a random number between 1 and 2. In (5), Q denotes the moving step size that decreases from 2 to 1 as the number of iterations t increases. BFGO simulates the behavior of bamboo whips randomly lengthening and expanding their territories underground on this stage, and guides the population to explore extensively in the solution space through a multi-directional and large-scale search mechanism to avoid the algorithm from falling into local optimal solutions. During the bamboo shoot growth stage, a temporary population is defined to replace the original population, which is defined by the following equations:

$$X_D = 1 - \left| \frac{X_t - C(k) + 1}{X_G - C(k) + 1} \right| \tag{6}$$

$$q(t) = X_G \times e^{-d} \times e^{\frac{b}{\varphi \times t^{\varphi}}} \tag{7}$$

$$\Delta H = \frac{q(t) - q(t-1)}{X_G - X_t} \tag{8}$$

$$X_{temp} = \begin{cases} X_t + X_D \times \Delta H \\ X_t - X_D \times \Delta H \end{cases} \tag{9}$$

Where X_D denotes the relationship between the distance of the particle to the population center position and the distance of the best individual of the population to the population center position, $q(t)$ denotes the cumulative growth of the t-th iteration, and ΔH denotes the incremental increase of one iteration. d is a parameter in the range of (-1, 1), and both b and φ are fixed parameters representing the site conditions of the bamboo.

Equation (7) is derived using the differential equation for the variation of bamboo height with growth [13] derived by Sloboda [14] and the integral form and its simplified equation to give, which can be expressed as follow:

$$\frac{dy}{dt} = \frac{m \times y}{t^l ln\left(\frac{n}{y}\right)} \tag{10}$$

$$y = n \times e^{-C} \times e^{\frac{m}{(l-1) \times t^{(l-1)}}} \tag{11}$$

$$y = SI \times e^{\frac{m}{k \times t^k}} \tag{12}$$

Where l, m, n are the parameters of the growth model, and ensure that l >1, m >0, n >0, t represents the growth time, y is the growth height of bamboo shoots. C is an integral constants. SI represents the maximum achievable bamboo height, which varies with changes in site conditions, and k is the alternative parameter after model simplification.

In this stage, BFGO emulates the process of bamboo shoots breaking out of the ground and growing randomly to become bamboos, and utilizes the height growth model to randomly update the location for individuals to enhance exploitation. However, the model is not applicable, the moving direction is blind, and the algorithm's local exploitation ability is deficient from the experimental results.

III. E-BFGO

A. Initialization

E-BFGO introduces the attribute of age for each individual in the initialization phase, and its value will be increased by 1 at the end of each iteration, in addition to which, all individuals will move independently in the extension and growth phases as a bamboo whip individual and a bamboo shoot individual, respectively, instead of participating in the extension and growth phases uniformly. Subsequently, each of the two types of individuals will be divided into K clusters, and the initial values of the individuals are mapped into the solution space by generating chaotic sequences successively from the Logistic mapping equations [15], [16], the form of the equations as well as the population initialization are designed as shown in (13) and (14):

$$w_{n+1} = \ r \times w_n \times (1 - w_n) \tag{13}$$

$$x_n = \ x_{min} + \ w_n \times (x_{max} - x_{min}) \tag{14}$$

Where r is a control parameter, w_n denotes the n-th chaotic sequence value, and x_n is the initial value of the n-th individual; with this initialization method the population can be made more uniformly distributed in the solution space with higher randomness.

B. Extended Bamboo Whip Extension Stage

As the underground stem system of bamboo, the surface of bamboo whip is densely covered with absorbing roots that can absorb water and mineral nutrients from the soil for supporting its own faster extension. Accordingly, the soil nutrient index SN is included in the extension stage in (15):

$$SN = BN \times e^{-0.5 \frac{t}{T}} \tag{15}$$

Where BN is the soil base nutrient, which decreases with increasing time. The equation for the movement of bamboo whips is subsequently rewritten as:

$$X_{t+1} = \begin{cases} X_G + Q \times S \times (X_G - X_t) \times cos\alpha, & r_1 < 0.4 \\ X_P(k) + Q \times S \times (X_P(k) - X_t) \times cos\beta, & 0.4 \leq r_2 < 0.7 \\ C(k) + Q \times S \times (C(k) - X_t) \times cos\gamma, & else \end{cases} \tag{16}$$

$$S = (0.7 \times SN + 0.3 \times \frac{T_s}{L_t})^Q \tag{17}$$

Where S is the length of the new moving step, T_s and L_t denote the age of bamboo shoots breaking the soil and the age of individuals, respectively. This implies that the movement of individual bamboo shoots is affected by soil conditions as well as growth time, and that individuals at the early stage of growth are the fastest to extend in all directions.

At the end of the extension phase, a small randomized perturbation is applied to each individual, replacing the original individual with a new, better one, as a way to enhance the algorithm's local search ability in the bamboo whip extension stage, Its form is shown in (18):

$$X_{Wt}' = X_{Wt} + \delta, \delta \in \left[\frac{X_{min}}{5 \times (X_{max} - X_{min})}, \frac{X_{max}}{5 \times (X_{max} - X_{min})}\right] \tag{18}$$

C. Extended Bamboo Shoot Growth Stage

Due to the limited optimization effect of the original growth strategy, the original strategy is replaced with new growth strategy. When the age of the individual bamboo whip reaches T_s, the individual will break through the soil layer and become a bamboo shoot, growing gradually active.

Shi et al. [13] used the growth data of 90 typical Moso bamboo samples to give the measured growth curve of bamboo shoots, as shown in Fig. 1.

We can find from the figure that the growth of this Moso bamboo shoot span a total of 57 days, and can be divided into three distinct stages: an initial phase of slow growth, followed by a stage of explosive growth, and finally a third stage where growth stabilizes. If modeled using (12), the growth pattern of the third stage cannot be accurately captured; instead, the model predicts continued growth. Logistic growth model [16] is one of the most widely used models to describe the changes in biomass and body length data of plants and animals, and it is highly compatible with the "S-shaped growth curve" of the

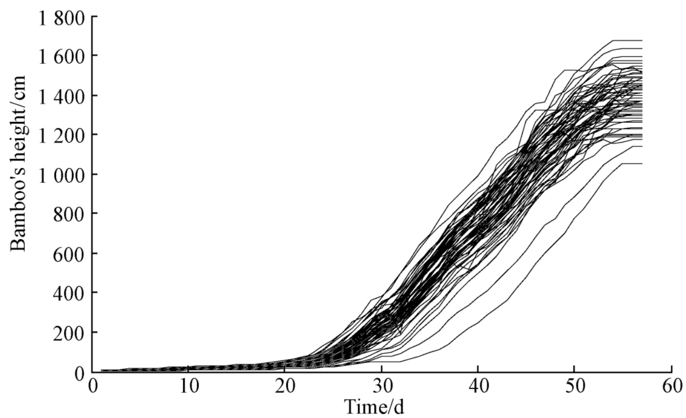

Fig. 1. Bamboo Shoots Growth Curve

individual height of bamboo shoot, which shows a "slow-fast-slow" trend [17]. Fig. 2 compares our Logistic growth model and the original model, both constructed through fitting based on data from Fig. 1. By extending the growth period to 80 days, a clear differentiation between them is demonstrated.

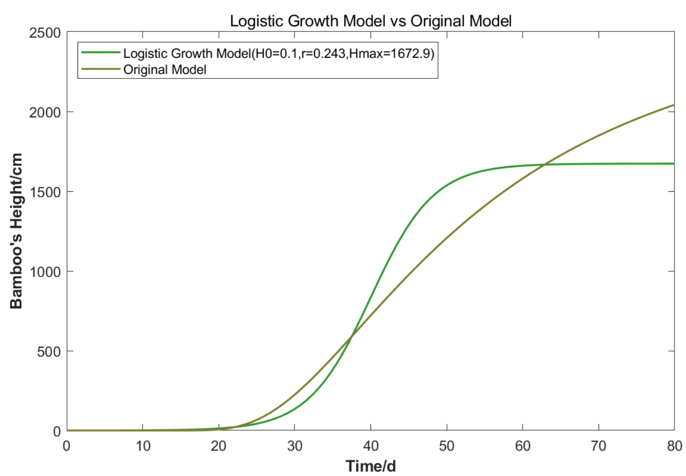

Fig. 2. Logistic Growth Model vs Original Model

Clearly, the Logistic growth model is more appropriate for capturing the growth traits of bamboo. Therefore, Sloboda's bamboo height growth model is replaced in this paper with a logistic model, whose differential form and equation for bamboo shoot individual growth are as follows:

$$\frac{dh}{dt} = r \times h \times \frac{H_{max} - h}{H_{max}} \tag{19}$$

$$\begin{gathered} X_{St+1} = X_{St} + (0.5 \times LN + 0.5 \times SN) \times \\ \left(\frac{X_G - X_{St}}{\|X_G - X_{St}\|} \odot |X_{St} - C(k)| \right) \times \frac{\|X_G - X_{St}\|}{\|X_G - C(k)\|} \end{gathered} \tag{20}$$

In (19), r represents the growth rate, h denotes the current height of the individual bamboo plant, and H_{max} is the maximum achievable height. $r \times h$ indicates the individual's current growth capacity, while $\frac{H_{max}-h}{H_{max}}$ reflects the degree of growth resistance encountered.

In (20), the global optimum position X_G guides individual movement, then $X_G - C(k)$ represents H_{max} and $X_S - C(k)$ represents h. By establishing the growth model in (19) as the baseline increment, both the light index LN and soil nutrient index SN serve as movement increments for this stage while coordinating growth rates. Just as light and nutrients play a central regulatory role in plant growth, having sufficient light and nutrients can promote the accumulation of organic substances such as sugars and provide an energy base for the bamboo shoots to sprout and thrive. The calculation of LN is as (21):

$$LN(k) = GL \times \frac{rank(k)}{K} \tag{21}$$

Where GL represents the global light index, which is taken randomly at each iteration. $rank(k)$ is the fitness ranking of the k-th cluster where an individual is located among the K clusters, and clusters with better fitness values receive more suitable light ,thereby growing more rapidly.

In addition, Wang et al. modeled bamboo according to its natural morphological structure using fractal graphic techniques [18], and they found that bamboo has typical fractal features, the ratio of the angle between most bamboo branches and the growth axis to the right angle approximates the golden section ratio, and they constructed the rotation matrix of the branches in three dimensions. A fractal model for individual bamboo shoots is accordingly designed to simulate the branching during the growth of bamboo joints in (22) – (25):

$$X_{St}' = \begin{cases} X_{St} + randn \times R \times \begin{bmatrix} bl \\ 0 \end{bmatrix}, & r_2 < 0.3 \\ X_{St} + randn \times R \times \begin{bmatrix} 0 \\ bl \end{bmatrix}, & 0.3 \le r_2 < 0.6 \\ X_{St}, & else \end{cases} \tag{22}$$

$$R = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \tag{23}$$

$$\theta = 34.14 \times \frac{\pi}{180} \tag{24}$$

$$bl = \mu \times \left\| \frac{X_{St}}{X_{St_{max}}} \right\| \tag{25}$$

Where R is the rotation matrix, θ is the rotation angle, bl represents the modal length of bamboo branches, and μ is a parameter in the range of (0,1). The growing bamboo shoot individuals will have a higher probability of growing branches in multiple random two-dimensional directions, and the excellent individuals with bamboo branches will replace the normal ones, while there will also exist some bamboo shoot individuals without bamboo branches.

D. Natural Selection Mechanism

The Forest Optimization Algorithm (FOA) developed a selection mechanism for population renewal and elite retention [19], which ranked candidate solutions from best to worst in terms of fitness, removed trees exceeding the age limit and selects superior solutions. By referring to this, at the end of each iteration, natural selection is performed on the whole population. The individuals in each cluster are sorted by fitness value, and a certain number of weak individuals are proportionally eliminated within the cluster based on a set elimination rate. In addition, individuals whose age reaches a set number of years are eliminated.If the eliminated individuals have already grown bamboo shoots, they will be replaced by new individuals, and the generation of new individuals will follow the initialization method. In this way, a natural replacement is accomplished, retaining the young elite individuals and avoiding a certain amount of poor quality solutions that continue to occupy resources. The clearer steps can be viewed from the pseudo-code.

E. Algorithmic Procedure

The pseudo-code of the E-BFGO algorithm as shown in Algorithm 1.

IV. Experiment and Analysis

This section will provide a comprehensive evaluation of the optimization performance of the E-BFGO algorithm and compare it with the original algorithm and some classical and improved algorithms, including PSO [20], VPPSO [21], SCA [22], EDOLSCA [23], GA [24], ALO [25], DE [26].

In the comparative experiment, a total of 30 benchmark functions from CEC2017 and 28 benchmark functions from CEC2013 [27] are employed for testing, which contain various types of single-peak, basic multimodal, hybrid, and combinatorial functions with different levels of difficulty and characteristics to comprehensively calibrate the algorithm's ability to deal with complex problems.

The search range of all test functions is [-100,100], the search dimensions is set to 50 dimensions, the population size is set to 30, and each algorithm is independently experimented 20 times. To ensure the test results are fair, the maximum number of evaluations for all algorithms is set to 15000.

Table I show the means of each algorithm on the CEC2017 test set, and table II show the means of each algorithm on the CEC2013 test set, respectively. Where the optimal results are bolded, the number of times E-BFGO outperforms other algorithms on all test functions is denoted by win.

According to the results, it can be seen that E-BFGO achieves the most optimal number of times, which shows that E-BFGO has strong competitiveness. Compared with the original algorithm, the performance of E-BFGO has been effectively improved in all kinds of test functions, and its global exploration and local development ability has also been improved, which makes it more adaptable to face complex problems.

Algorithm 1: Pseudocode of E-BFGO

Input: N:population size, D:dimension, It:the number of function iterations, $[lb, ub]$:problem boundary
Output: the best solution X_G

Initialize number of clusters K, base soil nutrition BN, age of bamboo L_n, time of growing into bamboo shoot T_s, time of death T_{end}, elimination rate α.
Initialize the bamboo whip position X_W_t and the bamboo shoot position X_S_t using Equations (13)–(14), then divide the bamboo whip population into K clusters in alternating order based on fitness and replicate them to the bamboo shoot population
while *t <It* **do**
    if X_G *not updated* **then**
        select some elite individuals and poor individuals to update X_W_t, X_S_t, and update X_P, X_G.
    end if
    if X_P *not updated* **then**
        redivide the population in alternating order.
    end if
    Set soil nutrition SN based on Equation (15).
    Update X_W_t according to Equations (16)–(17), and add disturbance to X_W_t based on Equation (18).
    Update X_P and X_G.
    if $L_n \geq T_s$ **then**
        Sort bamboo shoot clusters according to the average fitness, set global light GL.
        Update X_S_t according to Equations (20)–(21).
        while $d \leq D$ **do**
            using Equations (22)–(25) to make X_S_t grow branches.
            d = d + 2.
        end while
        if *r3 <0.8* **then**
            Select X_S_t with branches.
        else
            Select X_S_t without branches.
        end if
    end if
    Sort individuals within cluster accoring to their fitness, and elimitate $\alpha \times N$ poor individuals.
    Eliminate individuals with L_n greater than or equal to T_{end}.
    Generate new individuals using Equations (13)–(14) to replace eliminated individuals.
    Update X_P and X_G.
    t = t + 1, L_n = L_n + 1, and redivide the population into K clusters in alternating order based on fitness.
end while

TABLE I
COMPARISON OF TEST RESULTS OF VARIOUS ALGORITHMS ON 50 DIMENSIONS OF CEC2017

Test function	**PSO** Mean	**VPPSO** Mean	**SCA** Mean	**EDOLSCA** Mean	**GA** Mean	**ALO** Mean	**DE** Mean	**BFGO** Mean	**E-BFGO** Mean
F1	3.861E+10	2.682E+09	6.707E+10	3.903E+10	6.582E+10	1.824E+09	6.210E+09	2.475E+10	**9.232E+08**
F2	1.008E+68	1.123E+51	6.029E+69	7.080E+66	1.541E+71	2.452E+53	5.563E+58	1.885E+65	**1.351E+50**
F3	3.012E+05	1.742E+05	2.236E+05	2.598E+05	1.616E+05	3.516E+05	4.787E+05	2.698E+05	**1.069E+05**
F4	4.251E+03	1.117E+03	1.436E+04	6.010E+03	1.680E+04	9.927E+02	1.414E+03	4.428E+03	**8.889E+02**
F5	1.074E+03	8.253E+02	1.131E+03	1.089E+03	1.076E+03	8.874E+02	9.578E+02	9.660E+02	**8.208E+02**
F6	6.612E+02	6.608E+02	6.820E+02	6.760E+02	6.880E+02	6.596E+02	**6.177E+02**	6.769E+02	6.472E+02
F7	2.812E+03	1.521E+03	1.870E+03	1.905E+03	1.726E+03	1.746E+03	1.334E+03	1.662E+03	**1.233E+03**
F8	1.370E+03	1.143E+03	1.463E+03	1.391E+03	1.396E+03	1.169E+03	1.258E+03	1.316E+03	**1.134E+03**
F9	1.900E+04	1.156E+04	3.334E+04	3.533E+04	2.977E+04	1.540E+04	**8.868E+03**	2.684E+04	1.175E+04
F10	1.534E+04	**8.328E+03**	1.552E+04	1.382E+04	1.410E+04	8.987E+03	1.578E+04	1.190E+04	8.885E+03
F11	1.082E+04	3.216E+03	1.276E+04	1.202E+04	1.598E+04	3.818E+03	4.625E+03	7.653E+03	**2.058E+03**
F12	8.454E+09	2.716E+08	2.208E+10	9.682E+09	4.195E+10	**2.399E+08**	3.862E+08	7.233E+09	3.234E+08
F13	2.790E+09	1.085E+05	6.227E+09	2.848E+09	1.830E+10	**1.013E+05**	7.443E+06	1.977E+09	2.065E+05
F14	3.706E+06	7.841E+05	7.945E+06	3.288E+06	2.296E+07	9.054E+05	4.671E+05	6.396E+06	**3.241E+05**
F15	8.646E+08	**3.340E+04**	1.247E+09	2.671E+08	1.636E+09	5.432E+04	3.455E+04	5.816E+07	4.446E+04
F16	6.024E+03	3.897E+03	6.326E+03	5.028E+03	7.306E+03	4.373E+03	5.409E+03	6.091E+03	**3.666E+03**
F17	5.697E+03	3.621E+03	5.098E+03	4.075E+03	4.483E+03	3.796E+03	4.254E+03	3.916E+03	**3.423E+03**
F18	3.603E+07	5.742E+06	5.660E+07	2.534E+07	4.626E+07	5.331E+06	**2.941E+06**	1.170E+07	2.975E+06
F19	4.468E+08	1.558E+06	7.273E+08	2.870E+08	5.770E+08	3.535E+06	4.960E+05	2.085E+07	**5.580E+04**
F20	4.275E+03	3.286E+03	4.289E+03	3.942E+03	3.786E+03	3.473E+03	4.329E+03	3.665E+03	**3.281E+03**
F21	2.857E+03	2.647E+03	2.947E+03	2.861E+03	3.082E+03	2.638E+03	2.756E+03	2.907E+03	**2.634E+03**
F22	1.690E+04	1.036E+04	1.731E+04	1.557E+04	1.591E+04	1.110E+04	1.728E+04	1.444E+04	**1.035E+04**
F23	3.295E+03	3.187E+03	3.724E+03	3.744E+03	4.346E+03	3.300E+03	3.248E+03	4.087E+03	**3.157E+03**
F24	3.384E+03	**3.329E+03**	3.918E+03	4.003E+03	4.689E+03	3.430E+03	3.448E+03	4.228E+03	3.371E+03
F25	6.944E+03	3.514E+03	8.816E+03	6.853E+03	9.305E+03	3.512E+03	3.573E+03	5.630E+03	**3.347E+03**
F26	9.646E+03	1.024E+04	1.348E+04	1.258E+04	1.430E+04	9.910E+03	8.973E+03	1.282E+04	**7.991E+03**
F27	3.971E+03	3.948E+03	4.931E+03	4.855E+03	6.468E+03	4.369E+03	**3.200E+03**	3.747E+03	3.942E+03
F28	6.413E+03	4.279E+03	8.776E+03	7.213E+03	8.971E+03	4.445E+03	**3.313E+03**	5.789E+03	3.755E+03
F29	7.164E+03	6.184E+03	8.916E+03	6.963E+03	1.486E+04	7.022E+03	5.785E+03	8.687E+03	**5.533E+03**
F30	7.887E+08	1.390E+08	1.414E+09	4.332E+08	1.648E+09	1.412E+08	**6.791E+04**	2.723E+08	4.125E+07
Win	**30**	**24**	**30**	**30**	**30**	**28**	**23**	**29**	**-**

TABLE II
COMPARISON OF TEST RESULTS OF VARIOUS ALGORITHMS ON 50 DIMENSIONS OF CEC2013

Test function	**PSO** Mean	**VPPSO** Mean	**SCA** Mean	**EDOLSCA** Mean	**GA** Mean	**ALO** Mean	**DE** Mean	**BFGO** Mean	**E-BFGO** Mean
F1	2.801E+04	-3.359E+02	4.463E+04	2.465E+04	4.467E+04	-4.735E+02	2.308E+03	1.608E+04	**-1.043E+03**
F2	5.455E+08	6.384E+07	8.525E+08	3.202E+08	9.093E+08	6.942E+07	7.099E+07	2.203E+08	**5.909E+07**
F3	1.078E+11	4.025E+10	5.938E+11	2.872E+11	1.360E+12	6.668E+10	6.040E+10	1.115E+11	**2.837E+10**
F4	1.579E+05	8.413E+04	1.126E+05	1.383E+05	8.193E+04	1.608E+05	2.223E+05	1.164E+05	**5.935E+04**
F5	9.724E+03	-4.204E+02	5.893E+03	2.440E+03	5.841E+03	-2.911E+02	6.338E+02	1.815E+03	**-5.268E+02**
F6	8.142E+02	-5.298E+02	2.566E+03	4.850E+02	3.197E+03	-6.202E+02	-5.372E+02	1.739E+02	**-6.244E+02**
F7	-5.671E+02	-6.562E+02	-3.913E+02	-5.421E+02	6.367E+01	-2.433E+02	-6.057E+02	-2.381E+02	**-6.575E+02**
F8	-6.788E+02	**-6.788E+02**	-6.788E+02	-6.787E+02	-6.788E+02	-6.787E+02	-6.787E+02	-6.787E+02	-6.788E+02
F9	-5.247E+02	**-5.423E+02**	-5.225E+02	-5.330E+02	-5.292E+02	-5.374E+02	-5.220E+02	-5.296E+02	-5.364E+02
F10	4.032E+03	1.136E+02	5.796E+03	2.788E+03	6.020E+03	1.889E+01	3.907E+02	1.687E+03	**-9.598E+01**
F11	4.416E+02	1.214E+02	4.763E+02	3.835E+02	5.214E+02	2.505E+02	8.867E+00	4.249E+02	**-3.169E+01**
F12	5.125E+02	2.776E+02	5.930E+02	5.007E+02	7.003E+02	3.202E+02	2.515E+02	5.300E+02	**1.561E+02**
F13	6.187E+02	5.775E+02	7.282E+02	7.290E+02	7.721E+02	6.273E+02	**3.656E+02**	6.873E+02	4.008E+02
F14	1.481E+04	7.019E+03	1.446E+04	1.324E+04	1.354E+04	7.900E+03	1.491E+04	1.097E+04	**5.138E+03**
F15	1.521E+04	**8.295E+03**	1.542E+04	1.449E+04	1.460E+04	9.545E+03	1.546E+04	1.308E+04	9.745E+03
F16	2.044E+02	**2.010E+02**	2.044E+02	2.047E+02	2.040E+02	2.016E+02	2.046E+02	2.041E+02	2.025E+02
F17	2.359E+03	1.094E+03	1.506E+03	1.487E+03	1.382E+03	1.503E+03	9.300E+02	1.392E+03	**8.417E+02**
F18	2.511E+03	1.202E+03	1.620E+03	1.613E+03	1.484E+03	1.583E+03	1.076E+03	1.300E+03	**9.812E+02**
F19	2.674E+04	6.681E+02	2.829E+05	7.947E+04	2.048E+05	6.092E+02	1.430E+04	3.146E+04	**5.820E+02**
F20	6.247E+02	6.240E+02	6.247E+02	6.245E+02	6.247E+02	6.245E+02	6.239E+02	6.245E+02	**6.236E+02**
F21	4.441E+03	3.337E+03	4.977E+03	4.493E+03	4.614E+03	2.541E+03	3.335E+03	4.131E+03	**2.237E+03**
F22	1.602E+04	1.012E+04	1.645E+04	1.531E+04	1.639E+04	1.151E+04	1.613E+04	1.388E+04	**7.111E+03**
F23	1.641E+04	**1.148E+04**	1.692E+04	1.576E+04	1.695E+04	1.282E+04	1.693E+04	1.539E+04	1.179E+04
F24	1.399E+03	**1.369E+03**	1.442E+03	1.428E+03	1.592E+03	1.396E+03	1.397E+03	1.388E+03	1.381E+03
F25	1.539E+03	1.504E+03	1.567E+03	1.613E+03	1.685E+03	1.639E+03	1.495E+03	**1.485E+03**	1.523E+03
F26	1.662E+03	1.612E+03	1.700E+03	1.616E+03	1.652E+03	1.657E+03	1.697E+03	1.684E+03	**1.609E+03**
F27	3.532E+03	**3.204E+03**	3.747E+03	3.588E+03	4.033E+03	3.359E+03	3.560E+03	3.550E+03	3.322E+03
F28	5.718E+03	6.105E+03	8.233E+03	6.930E+03	9.614E+03	7.015E+03	4.465E+03	8.640E+03	**2.910E+03**
Win	**28**	**20**	**27**	**28**	**27**	**25**	**26**	**27**	**-**

V. Conclusion

In this paper, inspired by the growth characteristics and natural laws of bamboo forests, the original BFGO algorithm is expanded and replaced with more innovative strategies, while retaining some of the original algorithm's excellent mechanisms. The improved algorithm significantly enhances the performance of the original algorithm in terms of global search and local exploration. Its performance is compared with BFGO and some classical meta-heuristics and variants in two test sets, CEC2017 and CEC2013, and the test results show that the E-BFGO algorithm is highly competitive.

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