Research on Glowworm Swarm Optimization with Ethnic Division

Huabei Nie and Jianqiao Shen
City College of DongGuan University of Technology, Dong Guan, China

Xiaoping Li
Jiangxi Vocational College of Finance and Economics, Jiangxi, China

Abstract—Glowworm swarm optimization (GSO) algorithm is a new intelligent optimization algorithm. Based on the problems of GSO, such as easy to fall into local optimum, slow convergence speed and low optimization precision, an improved GSO with group division is presented. Using shuffled frog leaping algorithm (SFLA), glowworms are divided into different ethnic groups, and local search and global information exchange method improves the GSO performance. The mechanism based on particle position update mechanism in PSO is proposed in order to improve glowworm diversity. By using chaos optimization technique, glowworm groups are initialized, and the algorithm can obtain high quality initial solutions group. Finally, with the classical test functions, the simulation results show that, the GSO with hybrid behavior has better convergence speed and precision. According to the different types of firefly and cold light color is not the same, the glowworm swarm is divided into two sub group, to complete the aspects of paired glowworm swarm population quantity change. Then the cloth Valley bird search algorithm, cloth Valley bird by Levi to fly to the best way to choose size, this kind of flying mode with the machine more strong, will this flight mode into two populations of fireflies swarm evolutionary algorithm. Finish the fireflies optimization path of improvement.

Index Terms—Glowworm Swarm Optimization Algorithm; Shuffled Frog Leaping Algorithm; PSO; Chaos Optimization

I. INTRODUCTION

Research and application of intelligent optimization is one of the academic hot topics. As a lot of problem in the natural science and engineering technology field can be formulated as nonlinear global optimization problem, it has become an important research direction to seek a new swarm optimization algorithm having the intelligent characteristic and suitable for large scale parallel computation [1]. With the intelligent technology development, some novel swarm intelligence algorithms are put forward, such as Particle Swarm Optimization (PSO), Shuffled Frog Leaping Algorithm (SFLA), and Quantum Genetic Algorithm (QGA) and so on. By revealing or simulate natural phenomenon, intelligent optimization algorithm provides a new solution for solving complex problems.

Glowworm Swarm Optimization (GSO) [2] algorithm is a new swarm intelligence heuristic computing technology, derived from the biological phenomenon of firefly shining to attract mates and flying to the brightest individual, and has been successfully applied in noise test, multi-modal function optimization [3], analog robot [4], source location, cluster analysis of [5] etc.. Compared with particle swarm optimization algorithm, ant colony algorithm, and other traditional swarm intelligence optimization algorithms, GSO algorithm has rapid computing speed, less adjustable parameters, easy to realize [6], but the algorithm has defects such as slow convergence speed, accuracy is not high, easy to fall into local optimal solution. In order to improve the overall performance of the GSO algorithm, domestic and foreign scholars have conducted in-depth research, and achieved certain results. Based on the convergence of GSO algorithm, paper [7] validates the performance of GSO algorithm through the multi peak function simulation experiments. Paper [8] puts forward a hierarchical structure GSO algorithm, according to the human social stratification management ideas, which enhances the algorithm to solve high-dimensional function optimization problem ability. Paper [9] presents a glowworm swarm optimization algorithms with mating behavior, by introducing mating behavior and chaotic optimization technology, which improves the convergence speed and accuracy of GSO. These studies to some extent improve the performance of GSO algorithm. As GSO algorithm is a new swarm optimization algorithm, it still has much work to do for the algorithm improvement and application.

According to the basic glowworm swarm optimization shortcomings, based on SFLA ethnic division theory, the fireflies are divided into different ethnic groups. Based on the PSO particles move strategy, the firefly location updating mechanism is improved. By the use of chaos optimization technique, the firefly population is initialized. Further, this paper puts forward an improved glowworm swarm optimization algorithm: IGSO (Improved Glowworm Swarm Optimization, IGSO). And the simulation results show that the IGSO algorithm has better performance in the convergence speed and precision.
In the field of scientific computing and engineering problem solving, most people faced can be formulated as multi-objective optimization problem. With the rapid development and wide application of electronic computers, optimization technology to the rapid development, has been a research hotspot. In recent years, with the rapid development of intelligent computing theory and technology, people have put forward various bionic optimization algorithms, including genetic algorithm, ant colony algorithm, particle swarm optimization algorithm, simulated annealing algorithm, the algorithm in solving complex optimization problems have demonstrated excellent performance and great potential for development, therefore, research on Intelligent Algorithm is a has the important theory significance and the practical application value of the subject. The rest of the paper is organized as follows. Section 2 presents some basic GSO theories. Section 3 presents the details of improved GSO algorithm. Section 4 presents the simulation results [10].

II. BASIC GSO ALGORITHM

In 2005, based on swarm intelligence optimization theory, Krishnanand puts forward the glowworm swarm optimization algorithm. In the GSO algorithm, the fireflies are randomly distributed in the objective function solution spaces; each glowworm represents an optimization solution for the problem, and has their own decision domain [11]. The bioluminescence intensity of firefly is closed to the fluorescein that they carry on themselves, and the fluorescein is decided by the number of objective function of firefly, which means the objective function value more better the, the brightness of light more bigger. In the GSO algorithm, the firefly chooses the fireflies which have more fluorescein than itself in its decision scale to form set field, and flies to the individual in the set field with probability form. Related reaches show that GSO algorithm can converge to the global optimal [12, 13]. Figure 1 gives the basic principle of GSO algorithm.

![Figure 1. The basic principle of GSO](image)

In nature, the natural world of fireflies between individuals through the release of a called matter fluorescent pigment for information exchange, fireflies will release fluorescent element in the process of flight, from and fluorescent light, to attract around the his fireflies through fluorescent light. Fluorescent pigment concentration, fluorescence intensity is higher, it can attract more fireflies. From the enlightenment, the natural world fireflies as before, the GSO algorithm has been in many aspects to the success of the application. But is law there are some shortcomings, such as the method of operation of the later period still have shortcomings are easy to fall into local optimum and the convergence speed is slow, the lack of points in a certain extent hinder the artificial fireflies swarm optimization algorithm application range [15].

For a $n$ dimension function optimization problems, its solution space is $S = \{X \big| X = (x_1, x_2, \ldots, x_n)^T \} \subseteq \mathbb{R}^n$. We randomly generate an initial glowworm population consisting $N$ fireflies, and the $t$ generation of firefly groups can be described as $P = \{X_1(t), \ldots, X_k(t), \ldots, X_N(t)\}$, $k = 1, 2, \ldots, N$. The position of firefly $k$ is $X_k(t) = (x_{k1}(t), x_{k2}(t), \ldots, x_{kn}(t))$. We set up the fluorescein for firefly $k$ is $l_k(t)$, decision scale is $r_k^+(t)$ ($0 < r_k^+(t) < r_k^-$), and set field is $N_k(t)$. At the initial time, all fireflies have the same fluorescein $l_0$ and decision scale $r_0$.

A. Fluorescein $l_k(t)$ Update

Artificial glowworm swarm optimization algorithm is swarm intelligence is a novel can search algorithm, the simulation is the nature of the firefly using fluorescein into the line contact and to show social behavior [16]. Zai Ji of the GSO algorithm, fireflies $(i= 1, 2, 3, n)$ were randomly distributed in the $D$ dimension of target function of the search space. These fireflies released a known as fluorescent pigment material, from a fluorescent light. Fireflies emit fluorescent light through and around the fireflies for information exchange and they have their own decision-making domain. Each fireflies fluorescein intensity big small and fireflies their position on the target value of the associated, that is to say if the fireflies individual fluorescein value is greater, then show fireflies location is good, which is shown have a good target value; on the contrary, expressed the target value is poor. Fireflies were I in its decision in the range of choice of fluorescein value than the one high individual group into its neighbor set [17].

Concentrated in the adjacent domain I firefly, fluorescein value bigger neighbors have attracted greater force, absorbing the fireflies to move I. In addition, each firefly adjacent domain the number of individuals will affect its decision domain radius size, when the neighborhood range firefly a body density is small, the firefly decision domain radius increases in order to find a suitable number of neighbors; on the contrary, the firefly fire insect decision domain radius will shrink. In the end, most of the fireflies gather in a plurality of seats [18-20]. The firefly luminescence brightness is closely related to its location, and the objective function value is better, the brightness of light is bigger. Fluorescein uses dynamic updating mechanism, and the updating strategy is:

$$l_k(t+1) = (1-\rho)l_k(t) + \gamma f \left[ X_k(t) \right] \quad (1)$$
where, $\rho$ ($\rho \in (0,1)$) is fluorescein volatilization control coefficient, $\gamma$ is the objective function coefficient, and $f[X_i(t)]$ is the firefly objective function fitness value [21].

B. Fireflies Location $X_i(t)$ Update

Artificial glowworm swarm optimization algorithm in practice is still a kind of random search algorithm [22]. The algorithm execution is composed of groups of fireflies common cooperation finish, wherein each firefly independently in the candidate solution space searching required target solution, and find a solution to release certain fluorescein, the properties of the solution well, fireflies release of fluorescein fluorescence Su Qiang more, the greater the degree of solution is chosen to be the greater [23]. In the initial stage of algorithm with the position of the firefly fluorescein concentration is the same, with the algorithm, the better position of the fluorescein intensity bigger, gradually tends to convergence algorithm. In the firefly movement phase, firefly $X_i(t)$ chooses the individual $X_j(t)$ in the form of probability to move in its filed set, and the choice probability is:

$$p_{ij} = \frac{l_j(t) - l_i(t)}{\sum_{i \in N_j(t)} l_i(t) - l_j(t)}$$

(2)

When $X_j(t)$ is chosen, the $X_i(t)$ update mechanism is:

$$X_i(t+1) = X_i(t) + s \cdot e_i(t)$$

(3)

$$e_i(t) = s \left[ X_j(t) - X_i(t) \right] \left[ X_j(t) - X_i(t) \right]^T$$

(4)

where, $s$ is the location mobile step, and $\|X_j(t) - X_i(t)\|$ is the Euclidean distance.

C. Decision Scale $r^v_d(t)$ Update

Artificial glowworm swarm optimization algorithm and evolutionary algorithm for ten similar, use is based on population and global random search strategy, the algorithm does not need complex evolutionary operation, and is the basis of decision domain fireflies in a body set the search path. And swarm intelligence before can calculate method is compared, artificial glowworm swarm optimization algorithm in the consumption of memory and computing speed has obvious advantages, and the regulating parameters is less, is easy to realize. The algorithm has become intelligent computing research field in a new direction. At present the algorithm has been successfully applied to various surface [24].

The artificial fireflies swarm optimization algorithm, and the algorithm for multi-modal function optimization and machine human body. Also, how to move the signal source tracking, signal source location, optimization of multi-mode function, sensor noise test, simulated cluster machine crowd, analysis, numerical optimization calculation, knapsack problem and other aspects. The glowworm swarm optimization algorithm flow chart was shown in Figure 2. In the GSO algorithm, firefly will dynamically adjust its decision scale $r^v_d(t)$ according to the fireflies’ quantity. If the number of fireflies is excessive, It will narrow the decision scale, otherwise it will increase the level of decision scale. The decision control strategy is:

$$r^v_d(t+1) = \min \left\{ r^v_d(t), r^v_d(t) + \beta \left[ N_s - \left\lfloor N_s(t) \right\rfloor \right] \right\}$$

(4)

where, $\beta$ is the proportional coefficient, $N_s$ is the control parameters of firefly number within decision scale, and $\left\lfloor N_s(t) \right\rfloor$ is the number of fireflies for filed set.

![Figure 2. The glowworm swarm optimization algorithm flow chart](image)

III. IMPROVED GSO ALGORITHM

A. Ethnic Division

GSO algorithm essentially belongs to the category of random search algorithm. The GSO algorithm consists many firefly groups, and each firefly search for the optimal solution in the solution space. Fluorescein is communicated between different individuals, and the more fluorescein firefly has the selected probability is more bigger. As the fluoresce exchangement for GSO algorithm is restricted in the field set, the firefly groups are divided into a plurality of gathering area, which to a certain extent reduces the probability of GSO algorithm falling into local optimization. However, firefly having the very strong fluorescein is confined to the area within the field set and can only influence other individuals in its decision scale, so the fireflies around are unable to exchange fluorescein information, which means that the individual optimal information cannot be shared within the group, limiting the convergence speed. moreover, if the firefly having the very strong fluorescein is very close to the location of the local extreme points, then the
algorithm will be very difficult to jump out from the local optimum.

In order to improve the GSO algorithm search speed and avoid falling into local optimal solution, this paper using Population Division [9] ideas based on SFLA [10] algorithm, presents an improved GSO algorithm, IGSO algorithm will divide fireflies into different groups with the same group scale. In each group, firefly individual does local search, when all ethnic groups finish local searchment, all the fireflies are mixed, and are sorted based on the objective function of fitness value. Then fireflies are divided again in accordance with certain rules (as shown in Fig 3). This work does repeatedly, until the termination condition is satisfied.

The firefly population are sorted by the fitness values \( f(X_i(t)) \), and equally distributed into \( M \) groups. Each group frog number is \( Q (N=M \times Q) \). The first firefly put into the first ethnic group, second firefly put into the second ethnic groups, until the \( M \) firefly into the ethnic group. Then, the \( M+1 \) firefly is placed in the first ethnic group, the \( M+2 \) firefly are put into second ethnic group ... Until the finally firefly put into the \( M \) ethnic group.

![Figure 3. Ethnic division of GSO](image)

B. Improved Location Updating Mechanism

In order to improve the artificial fireflies swarm optimization algorithm of fast algorithm, and the searching speed, this chapter will population evolutionary algorithm for tribal organization structure into glowworm swarm optimization algorithm. The improved location updating mechanism takes firefly itself, the global optimal individual and the individual within filed set in consideration, which shows that firefly has social attribute. At each update, firefly dynamic tracking the location of the global best position, which makes the firefly can follow the current global optimal solution, and can increase the firefly search sample diversity, contributing to jump out of local optimal solution.

In the natural world, fireflies fly through the release of fluorescein cold light. By Yu Ying firefly is not same, cold light color fireflies emit is not the same, common cold light yellow and green color, the same kind of light color of the fireflies are gathering. The existing fireflies swarm optimization algorithm model, there is no cold light color to consider the problem of fireflies. Based on this, we proposed a with the two kinds of group of fireflies swarm into the algorithm. While in the cloth Valley bird search algorithm, as a random increase cloth Gu Niao optimization, algorithm makes use of a column dimension random high flying, the cuckoo optimization random greatly increase. The 5x5 processing time of 5 cases was shown in Table 1.

<table>
<thead>
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C. Chaos Optimization Algorithm (COA)

Chaos optimization algorithm [11] means expands chaos to the variables scope. COA uses chaos variables for global search and COA has good global search ability. Logistic mapping is the most used in the chaos optimization algorithm and logistic mapping has good randomness. The iterative equation for logistic mapping is:

\[ z_{n+1} = \mu \times z_n \times (1- z_n), 0 < z_n < 1 \]  \hspace{1cm} (6)

where \( \mu \) is a chaotic variable. In paper [12], when \( \mu \) value is among [3.85, 4], logistic mapping has the best performance. We give COA steps as follows:

Step1: Randomly generated a \( n \) dimension variable \( Z = [z_1, z_2, \cdots, z_n] \) ( \( 0 < z_i < 1 \) ). According to the equation (6), we get the chaotic initial variables \( Z \).

Step2: Expands chaos to the variables scope.

\[ x_i(t) = a_L + (a_U - a_L) \times z_{n_i} \]  \hspace{1cm} (7)

where \( a_L \) and \( a_U \) are the minimum and maximum values for frog \( X_i(t) \).

Step3: Does chaos search strategy.

Step4: Determine whether a termination condition is satisfied, if satisfied, end algorithm and output \( N \).
individuals has better values as GSO algorithm initial solutions group; otherwise, the iteration number plus 1, and moving to Step3.

This chapter presents a cloth Valley bird search algorithm cloth column dimension Valley bird optimization method of flying and fireflies swarm optimization algorithm combining the hybrid fireflies swarm optimization algorithm. This chapter will list dimension flying higher randomness into the GS O algorithm, GS O algorithm fireflies swarm optimization with better. Fireflies with machine better, then find possible optimum value also will greatly increase. Absorbing the cloth Valley bird search cloth advantages Valley bird optimization method, the properties of modified GS O algorithm is much improved. From the selected persuasive test function test results and flow to the problem solving, can get out of this chapter algorithm is correct and reliable.

D. IGSO Based on Ethnic Division

The algorithm has global convergence, but poor local searching ability, cause the algorithm in solving global optimization problems with the slow convergence speed, easily falling into local optimum, success rate of convergence and accuracy etc.. In this chapter, in order to improve GSO algorithm global optimization capability, will introduce chaos method and Powell method respectively to strong local searching ability of GSO algorithm, two improved glowworm swarm optimization algorithm is proposed, to balance the global convergence ability of the original algorithm and local optimization ability. The experimental results show that, the improved algorithm is very effective new method to solve the complex function optimization problems.

IGSO algorithm can be described as follows:

Step1: Parameter initialization. Initialize \( N, l_0, r_0, \rho, \gamma, s, \beta, N_j, M, Q, 0_l, 0_s, 0_o \) and \( \mu \). Set the algorithm global maximum iteration number \( T_{max} \).

Step2: Chaos initialization. With COA, initial solution group for IGSO is obtained.

Step3: Ethnic division. Calculate the firefly function fitness value, and according to 3.1, ethnic division is realized.

Step4: Groups search. For ethnic group \( m \), do local search ( \( m \) initial value is 1 ).

Step4.1: Fluorescein update. According to (1), all fireflies within groups update fluorescein.

Step4.2: Location update. According to (5), all fireflies within groups update location.

Step4.3: Decision scale update. According to (4), all fireflies within groups update decision scale.

Step4.4: Whether the ethnic termination condition is satisfied, if satisfied, turn to Step4.5, otherwise ethnic search iteration number plus 1, and moving to Step4.1.

Step4.5: Judge \( m \) is greater than \( M \) or not, if \( m > M \) move to Step5, otherwise, \( m = m + 1 \), and move to Step4.

Step5: whether the algorithm termination condition is satisfied, if satisfied, terminate the algorithm, and output the optimal results, otherwise, \( t = t + 1 \) and move to Step3.

IV. EXAMPLE SIMULATION

In order to verify the effectiveness of the IGSO algorithm, this paper selected 6 benchmark test functions, and takes the basic GSO algorithm for comparison, where \( f_1 - f_5 \) functions are from paper [13]. \( f_6 \) functions are from paper [14]. The 4 benchmark functions are:

1. Schaffer F6: \( x \in [-10,10] \). The function global minimum value is 0.

\[
f_1(x) = 0.5 + \frac{\sin^2 \sqrt{x_1^2 + x_2^2} - 0.5}{1 + 0.001(x_1^2 + x_2^2)^2}
\]

2. Six-hump Camel Back: \( x_i \in [-3,3], x_j \in [-2,2] \). The function global minimum value is -1.0316.

\[
f_2(x) = \left( 4 - 2.1x_1^2 + \frac{x_1^4}{3} \right) x_1^2 + x_1x_2 + (-4 + 4x_2^2)x_2^2
\]

3. BR-Branin: \( x_i \in [-5,10], x_j \in [0,15] \). \( x \in [-10,10] \). The function global minimum value is 0.398.

\[
f_3(x) = \left( x_2 - \frac{5.1}{4\pi^2} x_1^2 - \frac{x_1}{\pi} - 6 \right)^2 + 10\left( 1 - \frac{1}{8\pi} \right) \cos x_1 + 10
\]

4. Sphere: \( n = 20 \). The function global minimum value is 0.

\[
f_4(x) = \sum_{i=1}^{n} x_i^2, x_i \in [-100,100]
\]

In the Matlab simulation platform, we use GSO algorithm and IGSO algorithm to test the 6 functions. Paper [12] using uniform design method, GSO parameters setting is studied, and pointed out that when the GSO algorithm parameters take the following settings, its optimal performance is the best, and the specific parameters setting are: \( N = 200, l_0 = 5, \rho = 0.4, \gamma = 0.6, s = 0.03, \beta = 0.08, N_j = 5 \). At the initial time, \( r_j \) has the same value with \( r_i \), and for the 6 test functions, \( r_j \) values are taken as 10, 2, 10, 100, 500, 50. IGSO algorithm parameter settings are: \( M = 20, Q = 10, 0_l = 0.45, 0_s = 0.3, 0_o = 0.15, T_{max} = 500 \), \( I_{max} = 10 \), and other parameter settings are same with GSO algorithm. The 4 test functions are run 100 times. In order to obtain a better result, we take the mean value \( \bar{F} \) and average running time \( \bar{T} \) of 50 optimal experimental results for comparison. Table 2 gives the results of simulation experiments.

With the rapid development of science and technology, the optimization problem becomes more and more complicated, the scale is becoming larger and larger, only by an optimization algorithm is often difficult to solve or the relatively low accuracy, slow speed, therefore, to find a hybrid algorithm to solve the optimization problem has attracted many scholars study. The main idea of hybrid algorithm is a single algorithm from each other in performance optimization, optimization precision and optimization efficiency of the hybrid algorithm can

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generate better, to improve the performance of the algorithm. This chapter focuses on the complex function optimization problems, put forward a kind of artificial fish, artificial glowworm swarm and hybrid optimization algorithm based on evolution, experimental results show that the hybrid algorithm optimization, show the excellent performance of the.

In order to further compare GSO algorithm and IGSO algorithm, we propose a concept: success rate $V$, which means that if the test results is in the global optimal value precision range $\delta$, this test is called the successful operation, and the trials of successful operation number and all test number is called operation success rate. GSO algorithm and IGSO algorithm operation success rate $V$ and standard deviation results $S$ are shown in table 3.

| TABLE II. COMPARISON OF GSO AND IGSO |
|----------|----------|----------|
|          | GSO      | IGSO     |
| $f_1$    | 2.0332e-2| 1.34     | 1.2789e-4| 3.6     |
| $f_2$    | -1.2345e-1| 0.7     | -1.1246e-0| 2.6     |
| $f_3$    | 1.1823   | 2.2      | 3.2711e-1| 5.6     |
| $f_4$    | 1.2321e-4| 6.2      | 5.1445e-10| 3.2     |

In order to analyze the convergence speed and search ability, the algorithm convergence curve of average fitness value is provided in Figure 4-7 for the 4 test functions.

![f1 function convergence curves](image1)

In the basic artificial glowworm swarm optimization algorithm, each artificial firefly is randomly distributed in the objective function is defined in the space, the firefly has a respective fluorescein, and each one firefly has its own field of vision, we call the decision domain radius (local-decision range). Fluorescent brighter firefly says it location is better, that is the objective function which corresponds to the value is better. Firefly mobile way is: each firefly looking for areas within their respective scope of vision, find the fluoresce brighter fireflies in the field to move. Each moving direction can be changed by choosing different field. In addition, the decision region radius firefly will be affected according to the number of fields of fireflies are

![f2 function convergence curves](image2)

In the basic artificial glowworm swarm optimization algorithm, each artificial firefly is randomly distributed in the objective function is defined in the space, the firefly has a respective fluorescein, and each one firefly has its own field of vision, we call the decision domain radius (local-decision range). Fluorescent brighter firefly says it location is better, that is the objective function which corresponds to the value is better. Firefly mobile way is: each firefly looking for areas within their respective scope of vision, find the fluoresce brighter fireflies in the field to move. Each moving direction can be changed by choosing different field. In addition, the decision region radius firefly will be affected according to the number of fields of fireflies are
different, when the number of neighborhood firefly too little, firefly will increase the radius of their own so that the need for making more firefly; on the contrary, it will decrease the radius of their own decision. Finally, make the most of fireflies gather in a superior position.

![Graph](image1)

**Figure 6.** $f_1$ convergence curves

Artificial glowworm swarm optimization algorithm is a natural phenomenon source poly activities in the evening group in simulating natural fireflies and proposed, in the firefly group activities, the fireflies were foraging and courtship information exchange through the dissemination of fluorescein and peer. In general, the brighter the firefly luciferin its appeal is stronger, the final will be many fireflies gather around some fluorescein lighter fireflies. The glowworm algorithm is proposed according to the phenomenon of a kind of new bionic swarm intelligence optimization algorithm. In the artificial glowworm swarm optimization algorithm, each firefly is regarded as a solution space, firefly populations as the initial solution is randomly distributed in the search space and solution space, move each firefly mobile way according to the nature of fireflies. By moving each generation, the fireflies gather better fireflies around, that is to find multiple extreme points, so as to achieve population optimization objective.

![Graph](image2)

**Figure 7.** $f_4$ convergence curves

V. ALGORITHM PERFORMANCE ANALYSIS

From table 1, table 2 and figure 3-6, we can see that in solving precision IGSO is better than GSO. Especially for complex function, IGSO algorithm has higher accuracy. In the operation success rate and operational stability, for function $f_1$, $f_3$, $f_4$, IGSO success rate is 100%, and the solving complex function success rate and standard deviation of IGSO algorithm is smaller than GSO algorithm, that means IGSO algorithm has good stability and strong optimization ability. In the convergence speed, for low dimension, IGSO algorithm's convergence rate is slower than the GSO algorithm, but for high dimensional function, IGSO algorithm converges faster than GSO.

We focused on a single artificial glowworm swarm optimization algorithm for solving the low precision, slow convergence rates, will introduce the foraging behavior of artificial fish swarm algorithm to the artificial glowworm swarm optimization algorithm, and the differential evolution algorithm fusion, a double population evolutionary strategy, introducing an optimal information sharing mechanism, proposed a hybrid optimization algorithm. The simulation results show that the proposed algorithm, faster convergence rate, optimization of higher accuracy, better stability, and is very effective for optimization of multidimensional complex function and solving problems in engineering design.

The simulation results show that especially for complicated function optimization problem, IGSO algorithm shows good performance. This is because the IGSO algorithm divides fireflies into different ethnic groups. In solution of low dimensional function, population division consumes a part time, and reduces the convergence speed, but for complex functions with high dimensions, population division mode help IGSO jump out local optimum capacity, and improves the rate of convergence. In addition, the firefly location update improvement and chaotic improve the convergence speed and precision.

VI. CONCLUSIONS

This paper analyzes the basic GSO algorithm model and researches its shortcomings, then puts an improved GSO algorithm. Fireflies are divided into different groups, and the local search and global information exchange method improve the performance of the algorithm. The location strategy is improved, and the introduction of the chaos optimization technology, further improves the convergence speed and precision. The simulations results show that the improved GSO algorithm has better precision and convergence speed. Research on how to apply the chaos method, Powell method is introduced into the artificial glowworm swarm optimization algorithm, to effectively balance the global search ability of artificial glowworm swarm optimization algorithm and local optimization ability, and improve the precision and convergence rate. Research on how to apply the artificial fish swarm algorithm, differential evolution algorithm and artificial glowworm swarm optimization algorithm fusion, to overcome the disadvantages of artificial glowworm swarm optimization algorithm is easy to premature. Research on how to introduce the hybrid algorithm based on constraint handling technique feasibility rules based on local search and simulated annealing algorithm, and how to use the hybrid artificial glowworm swarm optimization algorithm to solve complex constrained optimization problems.
Experimental results show that, relative to other algorithms in the literature of the hybrid algorithm, optimization of higher accuracy, better stability.

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