An Improved Krill Herd Algorithm Based on Meme Grouping Strategy of Shuffled Frog Leaping Algorithm

Yu-Feng Sun, Jie-Sheng Wang, and Xiao-Xu Ma

***Abstract*—Krill herd (KH) algorithm is a new bionic intelligent algorithm which originates from the behavior of foraging krill. In order to enhance the search performance of KH algorithm, and further improve the convergence speed of the algorithm and optimization precision, an improved krill herd optimization algorithm based on the memes grouping strategy of shuffled frog leaping algorithm was proposed. The simulation experiments are carried out by using the six typical test functions to discuss the optimization performance. The simulation results show that the improved Krill herd algorithm can effectively increase the algorithm's convergence speed and optimization precision.**

***Index Terms*—krill herd algorithm, shuffled frog leaping algorithm, meme grouping, function optimization**

I. INTRODUCTION

OPTIMIZATION is the selection of a best element from a set of some available alternatives with regard to some criterion. The optimization algorithm is a basic principle of nature, which shows many different advantages and disadvantages in computational efficiency and global search probability and has a vast variety of applications in research and industry [1]. The function optimization presents a formalized framework for modelling and solving some certain problems. Given an objective function, it takes a number of parameters as its inputs, whose goal is to find the combination of parameters and return the best value. This framework is abstract enough that a wide variety of different problems can be interpreted as function optimization problems [2].

However, the traditional function optimization algorithms are used to solve the typical problem with small dimension, often not applicable in practice. So people focus on the nature. Nature provides rich models to solve these problems (such as fireflies, bats and ants). People proposed many swarm intelligence optimization algorithms by simulating the natural biological systems. These models could stimulate the computer scientists to use these non-traditional tools to solve the application problems [3]. Now a lot of swarm intelligence optimization algorithms are proposed, such as particle swarm optimization (PSO) algorithm [4], ant colony optimization (ACO) algorithm [5], bat algorithm (BA) [6], social learning optimization (SLO) algorithm [7], chickens swarm optimization (CSO) algorithm [8], firefly algorithm (FA) [9] etc. They can be used in the dictionary learning ON remote sensing data, automotive safety integrity level positioning, economic dispatch, and the cloud service composition of QOS awareness. Obviously, the study of swarm intelligence optimization algorithm has become an important research direction.

The krill herd (KH) algorithm is a new kind of bionic swarm intelligent algorithm based on the simulation of Antarctic krill group's movement in the marine environment [10]. It is a global probabilistic searching algorithm with simple operation, strong commonality, parallel processing and strong robustness, which has been widely used to solve the numerical function optimization problem and data clustering [11], the inverse radiation problem [12], the phase equilibrium calculation [13], the power flow optimization [14], the dynamic optimal power flow of combined heat and power system [15], the optimal power flow with direct current link placement problem [16], the turbine heat flow optimization with the fast learning network [17] and the inverse geometry design of two-dimensional complex radiative enclosures [18].

In order to enhance the search performance and further improve the convergence speed and optimization precision of KH algorithm, a improved KH-SFLA algorithm is put forward based on the principle of krill herd algorithm and shuffled frog leaping algorithm. Then the performance comparison and analysis are carried out through the simulation experiments in order to prove the superiority of the proposed hybrid algorithm. The paper is organized as follows. In Section 2, the krill herd algorithm is introduced. The principle of KH-SFLA is introduced in details in Section 3. The simulation experiments and results analysis is described in Section 4. Finally, the conclusion illustrates the last part.

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II. BASIC PRINCIPLE OF KRILL FORAGING ALGORITHM

A. Principles and Procedures of Krill Herd Algorithm

The KH algorithm was proposed by Amir Hossein Gandomi based on the simulation of the reaction of krill swarm in the process of evolution and environmental change. According to Darwinian evolutionary theory, the survival adaptability of krill individuals living in the sea is not only related to the distance from the food source location, but also related to whether they can be located in the vicinity of the area with the highest population density [19-21]. For the optimization problem in n dimensional space, the krill location is generally calculated by the following Lagrange model in KH algorithm.

$$\frac{dX_i}{dt} = N_i + F_i + D_i \tag{1}$$

where, N_i represents the movement induced by other krill individuals, F_i is the foraging activity, and D_i represents the random activities of individuals.

B. Movement Induced by Other Krill Individuals

Because the movement of individual krill will make the ethnic place changing all the time, in order to achieve the population transfer, all individuals will interact with each other. As a result, the ethnic swarm maintains a high degree of concentration. For a single krill, its movement direction α_i is restricted by many factors described in Eq. (2) and (3), such as nearby individuals, optimal individuals, and population exclusion, etc.

$$N_i^{new} = N^{\max}\alpha_i + \omega_n N_i^{old} \tag{2}$$

$$\alpha_i = \alpha_i^{local} + \alpha_i^{target} \tag{3}$$

where, $N^{\max}$ represents the maximum induced velocity (generally 0.01 m/s), ω_n is the inertia weight usually evaluated in the scope [0,1], and N_i^{old} is the last changed motion. α_i^{local} is the direction vector produced by the nearby individual and α_i^{target} is the target direction vector provided by the optimal krill individual.

In KH algorithm, the nearby krill populations impact on individuals. Generally, it can be reflected as attraction and exclusion. In detail, the formation of α_i^{local} can be calculated by the following equation.

$$\alpha_{\mathrm{i}}^{\mathrm{local}} = \sum_{\mathrm{j=1}}^{\mathrm{NN}} \hat{\mathrm{K}}_{\mathrm{ij}}\hat{\mathrm{X}}_{\mathrm{ij}} \tag{4}$$

$$\hat{X}_{ij} = \frac{X_j - X_i}{\|X_j - X_i\| + \varepsilon} \tag{5}$$

$$\hat{K}_{ij} = \frac{K_i - K_j}{K^{worst} - K^{best}} \tag{6}$$

where K^{best} is the current highest target function value, K^{worst} represents the lowest value of the fitness function, K_i represents the value of the target function corresponding to the ith krill individual, K_j is the fitness of jth ($j = (1, 2, \cdots, NN)$) neighbor, X represents the location of the krill and NN is the number of nearby individuals. For avoiding the singularities, a small positive number ε is added to the denominator.

There are many krill individuals around a single krill. According to the actual movement of krill population, a range is set around a single krill. Krill in this space are considered as the adjacent individual of the krill. The distribution diagram is shown in Fig. 1. The space radius is defined as follows [10]:

$$d_{s,i} = \frac{1}{5N}\sum_{j-1}^{N}\left\| X_i - X_j \right\| \tag{7}$$

where, $d_{s.i}$ represents the radius of the nearby individual of the i -th krill and N represents the number of total krill in the population.

In addition, for krill individuals nearby the optimal position in the population, the guiding direction vector of the i -th individual krill can retrieve the global optimal solution. The definition of this vector is defined as follows:

$$\alpha_i^{target} = C^{best}\hat{K}_{i,best}\hat{X}_{i,best} \tag{8}$$

where, C^{best} represents the effective degree parameter of the krill individual with the best fitness to the ith krill, whose calculation equation is described as follows.

$$C^{best} = 2\left(rand + \frac{I}{I_{\max}} \right) \tag{9}$$

where, $rand$ is a random value between 0 and 1, I is the current iteration number and $I_{\max}$ is the maximum number of iterations.

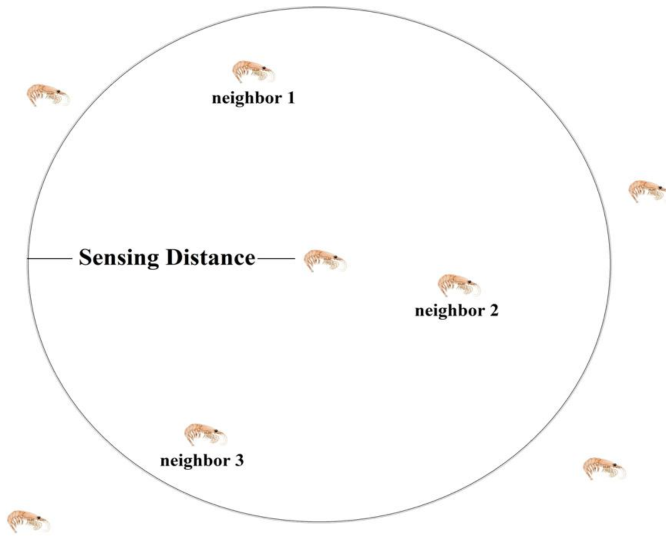


Fig.1 The distribution of krill individuals.

C. Foraging Activity

For krill individuals, two key factors usually influence their foraging activities: the location of the current food source and its last location [8]. Among the krill population, the number of individuals is N . The foraging activity of the ith individual krill can be expressed as:

$$F = V_f \beta_i + \omega_f F_i^{old} \tag{10}$$

$$\beta_i = \beta_i^{food} + \beta_i^{best} \tag{11}$$

where , V_f is the foraging speed, which is selected as 0.02 m/s [30], ω_f is the inertia weight generally locating in the interval [0,1], β_i^{food} is the direction vector of food attractive and β_i^{best} is the current best target function of the ith individual krill. In each iteration, the food source location is calculated by:

$$X_i^{food} = \frac{\sum_{i=1}^{N} \frac{1}{K_i} X_i}{\sum_{i=1}^{N} \frac{1}{K_i}} \tag{12}$$

$$\beta_i^{food} = C^{food} \hat{K}_{i,food} \hat{X}_{i,food} \tag{13}$$

where, C^{food} is the direction parameter. Because the attraction caused by food will gradually undermining, C^{food} is determined by:

$$C^{food} = 2\left(1 - \frac{I}{I_{\max}}\right) \tag{14}$$

In addition, the location orientation of the best krill individual β_i^{best} can be represented as:

$$\beta_i^{best} = \hat{K}_{i,best} \hat{X}_{i,best} \tag{15}$$

where, $K_{i,best}$ is the found best food location in the latest iteration of the ith krill individual.

Overall, in KH algorithm, the food source always attracts all individuals (the feasible solution) to move towards the optimal location (the optimal target function). After a large number of iterations, the individuals are concentrated around the best place (the best solution). Therefore, the foraging activity effectively improves the global detection performance of this algorithm.

D. Free Movement of Individual Krill

When each krill is swimming, it is affected by swarm migration and foraging activities, and it also generates random swimming patterns. The swimming state of krill individuals usually depends on the highest swimming speed and a higher random direction vector [10]. It can be expressed as:

$$D_i = D^{\max} \delta \tag{16}$$

where, $D^{\max}$ is the maximum diffusion speed of individual, and δ is a direction vector with high randomness, whose elements all randomly located in the scope [-1, 1]. Theoretically, the better the position of individual krill, the less significant the random diffusion.

With the change of time (i.e., the increase of iteration number), the migration and foraging activities of the population have less influence on the individual swimming of krill. To make the random walk of the individual gradually decrease with the change of time, a new variable should be introduced shown in Eq. (17).

$$D_i = D^{\max}\left(1 - \frac{I}{I_{\max}}\right)\delta \tag{17}$$

E. Motion Process of KH Algorithm

The above three factors can easily make different krill individuals change their positions towards the specific value of optimal fitness. That is to say, with the increase of iteration times, the feasible solution will gradually evolve into the optimal solution. The migration and foraging activities of the population include one of the local search strategies and the whole search strategies. When the two strategies are developed simultaneously, KH algorithm can be transformed into a stronger optimization algorithm. To sum up, through the above three behaviors, the actual position vector of krill individuals will be calculated according to the following equation during the interval t to $t + \Delta t$.

$$X(t + \Delta t) = X_i(t) + \Delta t \frac{dX_i}{dt} \tag{18}$$

where, Δt represents the specific gravity factor of the velocity vector. Its value is mainly determined by the search space.

$$\Delta t = C_t \sum_{j=1}^{NV} \left(UB_j - LB_j\right) \tag{19}$$

where, NV represents the total number of variable, LB_j and UB_j are lower and upper bounds of the jth variable ($j = 1, 2, \cdots, NV$). The absolute value of the subtraction indicates the overall category of searching space. The smaller the value, the smaller the search step size during the algorithm run.

III. KH-SFLA ALGORITHM

A. Principle of Shuffled Frog Leaping Algorithm

In 2003, the shuffled frog leaping algorithm (SFLA) had been proposed by Eusuff M etc [20]. It simulates the process of looking for food for frog groups by adopting the information exchange manner based on the classified ethnic thoughts. Memes algorithm (MA) is a swarm intelligence algorithm by heuristic search to solve the optimization problems established in 1989 by Moscato. SFLA integrates the advantages of MA and particle swarm optimization (PSO) algorithm, which achieved the equilibrium between the global exploring ability and local development ability. Every frog represents a solution of SFLA, and the frogs with the similar structure consist of a population [23]. The entire population is divided into multiple subgroups which are regarded as a collection of frogs having different ideas. In the process of implementation the local search implementation for each subgroup, every frog has their own thoughts, which is influenced by the ideas of the other frogs, and the subgroups concurrent evolution. When subgroups will be evolved to the local algebraic, each subgroup is mixed by using the information exchange between different subgroups, and the algorithm is proceeded with the local structure and global structure alternately until meeting the termination criteria [24].

For the problem of D dimension, a frog i can be expressed as $F_i=(f_{i1},f_{i2},\cdots,f_{iD})$. Firstly, the frog population S is initialized, the fitness of each frog is calculated and the frogs in the population are sorted in accordance with the descending order. Then the population is divided into m subgroups, which m satisfied $S=m\times n$. n is the number of frogs in each subgroup. Starting from the first subgroup, the first frog is selected. In turn, the corresponding frog is placed until the m -th frog is placed in the m -th subgroup. Furthermore, put the ($m+1$)-th frog into the first subgroup until the S -th frog is placed according to this way. Set a collection of frogs in the k -th mene class M^k. This allocation process can be represented as.

$$M^k=\left\{X_{k+m(l-1)}\in P\,|\,1\le l\le n\right\},1\le k\le m \tag{20}$$

The frogs with best and worst fitness in each subgroup are set as F_b and F_w. The frog with the best fitness in population is set as F_g. For each iteration evolution of subgroup, only update the position of F_w according to the following equation.

$$C_i=rand()\times(F_b-F_w) \tag{21}$$

$$F_w{}'=F_w+C_i(\|C_i\|\le C_{\max}) \tag{22}$$

where, $rand()\in[0,1]$ and $C_{\max}$ represents the maximum step length. The updated step length C_i is calculated by Eq. (21) and Eq. (22) is used to update the position of the worst frog F_w'. $C_{\max}$ represents maximum step length. If get a better solution, replace the worst individual with it. Otherwise, F_b replaces F_g in the Eq. (21) to carry out the calculation again. If still do not get a better solution after comparison, F_w' will be replaced with a new random generated solution. When complete the local search $L_{\max}$, the frogs of all subgroups are mixed. Then the frogs are sorted according to their fitness and the sorted frogs are divided into meme groups. Finally, enter the next round of local search and repeat the algorithm in this way, until meet the algorithm termination condition [25].

B. KH-SFLA Hybrid Algorithm

Although krill herd algorithm is a global probability search algorithm with simple operation, strong commonality, parallel processing and strong robustness. However, it is not hard to find its shortcoming of slow convergence speed and lower convergence precision by simulation experiments. The shuffled frog leaping algorithm (SFLA) combines the genetic of memes algorithm (MA) and colony foraging behavior of particle swarm optimization (PSO) algorithm together, which adopts the heuristic searching strategies together so as to improve the local search ability and stability rapidly. As a result, a hybrid KH-SFLA algorithm is proposed based on the krill herd algorithm and shuffled frog leaping algorithm. The idea of the improved algorithm is that the global and local search strategy of hybrid leapfrog algorithm and memes grouping thought are introduced in optimization process of the standard KH algorithm, which promotes the exploration ability of algorithm and accelerates the convergence speed. The procedure of proposed KH-SFLA algorithm is shown in Figure 2 [21].

The proposed KH-SFLA algorithm is on the basis of KH algorithm and the grouping idea of SFLA in the subgroup searching process. Set the optimum is K_b and the minimum is K_w. Then the candidates are grouped and carried out the local searching. According to the initial krill selection rule, the updating strategy can be described as follows.

$$C_i=rand()\times(K_b-K_w) \tag{23}$$

$$K_w{}'=K_w+C_i \tag{24}$$

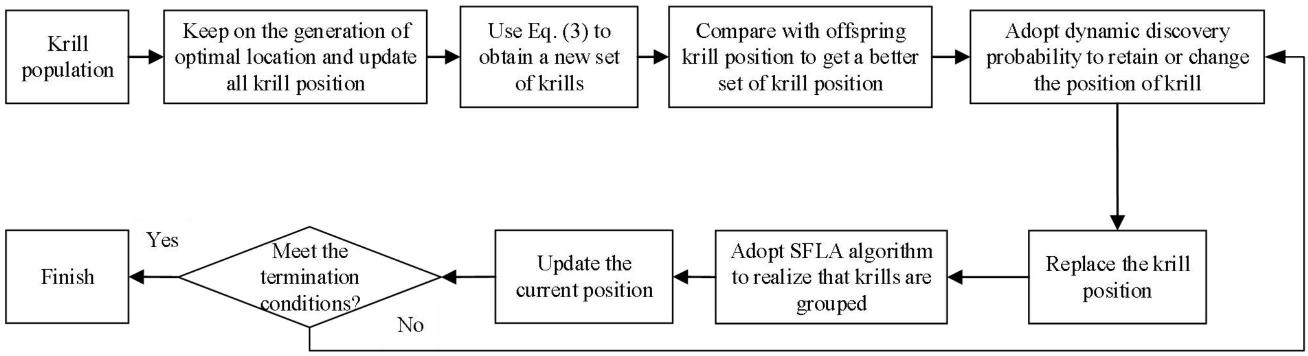


Fig. 2 Flowchart of KH-SFLA algorithm.

where $rand()$ is a random value between 0 and 1. The searching area of KH algorithm is increased by introducing the grouping search mechanism of shuffled frog leaping algorithm to some extent. The proposed KH-SFLA algorithm can quickly jump out of the local extreme value point and explore in the direction of the global optimal solution, which can greatly improve the optimization efficiency of the improved hybrid algorithm.

IV. Simulation Experiments and Results Analysis

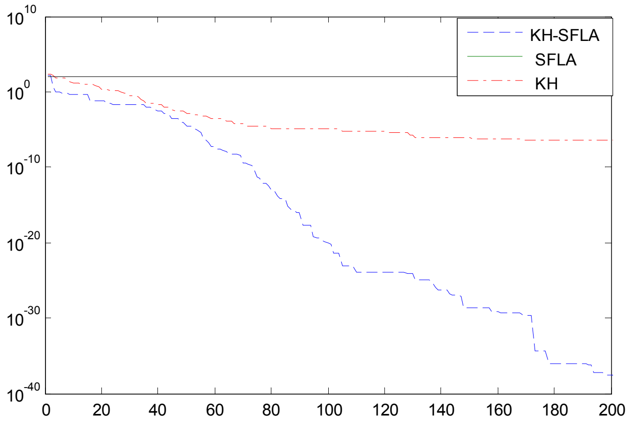
Six typical test functions listed in Table 1 are optimized by KH-SFLA, and the simulation results are compared with KH algorithm and SFLA. The algorithms are evaluated through statistical results (the optimal value, average value and run time) by running the procedure ten times. The convergence curves of six functions under three optimization methods are shown in Figure 3. The performance comparison results are listed in Table 2.

TABLE 1. SIMULATION TESTING FUNCTIONS

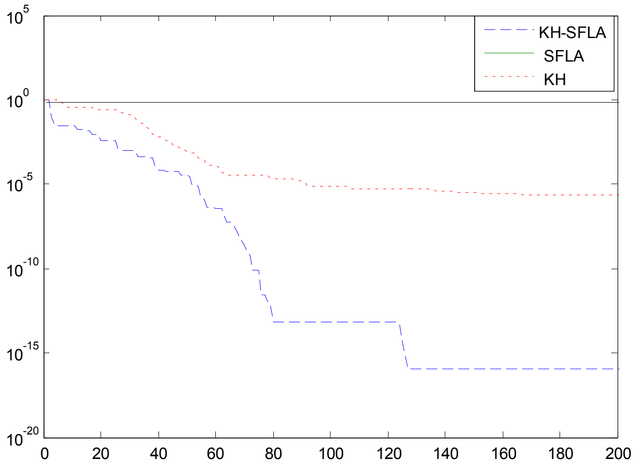
Function	Name	Expression	Range
f_1	Sphere	$f_1(x)=\sum_{i=1}^{d}x_i^2$	[-100, 100]
f_2	Griewank	$f_2(x)=\sum_{i=1}^{n}\frac{x_i^2}{4000}-\prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$	[-32, 32]
f_3	Ackley	$f_3(\mathrm{x})=-20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right)-\exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2px_i)\right)+20+e$	[-32, 32]
f_4	Michaelmas	$f_4(x)=-\sum_{i=1}^{d}\sin(x_i)\sin^{2m}(\frac{ix_i^2}{\pi})$	[0, π]
f_5	Schwefel	$f_3(x)=418.9829d-\sum_{i=1}^{d}x_i\sin(\sqrt{\lvert x_i\rvert})$	[-10, 10]
f_6	Rastrigin'	$f_6(x)=n*10+\sum_{i=1}^{d}(x_i^2-10\cos(2\pi x_i))$	[-5.12, 5.12]

TABLE 2. THE SIMULATION RESULT OF THREE ALGORITHMS

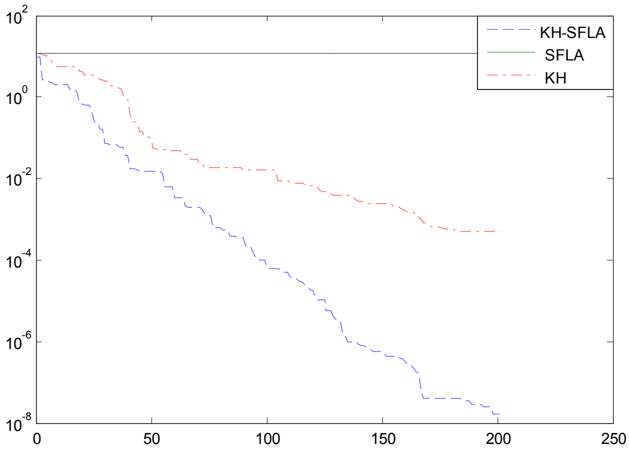
Function	Optimization algorithm	Optimum	Average	Run time (s)
Sphere	KH	3.392163e-007	1.146385e-005	3.925
	KH-SFLA	2.971876e-038	8.380115e-032	7.021
	SFLA	98.392874	1.629244e+002	3.080
Griewank	KH	2.254792e-006	0.014059	4.036
	KH-SFLA	1.110223e-016	1.276756e-015	7.484
	SFLA	0.747448	0.961522	3.251
Ackley	KH	5.047495e-004	0.878519	3.996
	KH-SFLA	1.687426e-008	4.233923e-008	7.176
	SFLA	11.743391	12.724539	3.246
Michaelmas	KH	-6.217428	-5.177968	3.732
	KH-SFLA	-9.568960	-6.502990	7.434
	SFLA	-7.049296	-3.580339	3.782
Schwefel	KH	4.150375e+003	4.150378e+003	3.527
	KH-SFLA	4.157143e+003	4.161386e+003	6.572
	SFLA	4.162553e+003	4.171366e+003	2.892
Rastrigin'	KH	4.976764	15.622917	4.134
	KH-SFLA	2.842170e-014	1.764988e-012	7.431
	SFLA	1.364816e+002	2.325955e+002	3.405



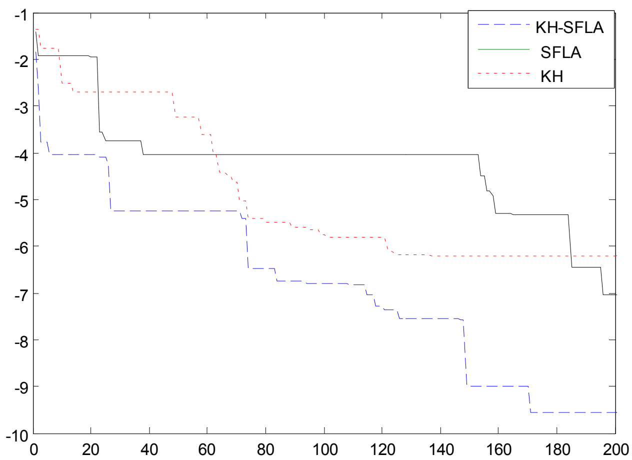
(a) f_1



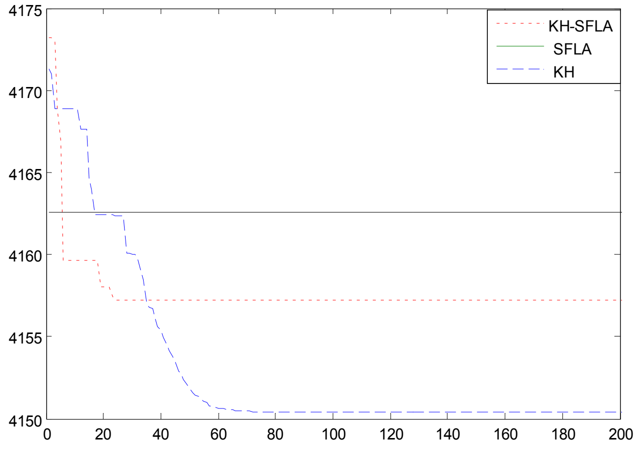
(b) f_2



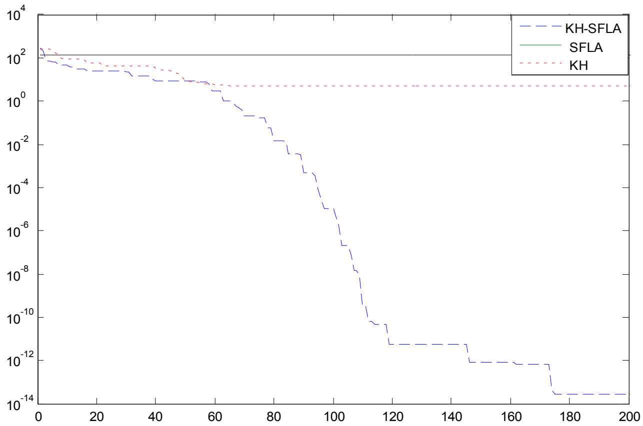
(c) f_3



(d) f_4



(e) f_5



(f) f_6

Fig. 3 Simulation results under different methods.

It can be seen from the simulation results that convergence speed and optimization accuracy of KH-SFLA is best and optimal solution is equal to or less than SFLA optimal solutions. It shows that the feasibility and efficiency of KH-SFLA optimization. At the same time the running time of the proposed hybrid algorithm were greater than KH and SFLA. It can be seen from the convergence curve comparison results for six functions that the convergence speed of the proposed algorithm gets obvious improvement. The precision of KH-SFLA algorithm is superior to SFLA and KH. The convergence rate is larger in the early stage, then the speed slows down and delays in the later. However, the algorithm remains a convergence trend, which does not affect the final optimization result for six functions. As a result, the improved algorithm makes the convergence speed and convergence accuracy getting better dramatically.

V. Conclusion

Krill herd optimization algorithm is a new swarm intelligence algorithm. In order to improve the convergence speed and optimization precision of KH algorithm, an improved krill herd optimization algorithm based on the memes grouping strategy of shuffled frog leaping algorithm was put forward. The adopted memes grouping strategy can make KH algorithm realize the more carefully and comprehensively search. The simulation experiments are carried out by using six benchmark functions. In order to verify the optimization performances of the improved algorithm, it is compared with KH algorithm and SFLA. The experiment results prove that the improved KH-SFLA algorithm has better convergence speed and optimization precision.

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