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An Effective Krill Herd Algorithm for Numerical Optimization

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Abstract

The krill herd (KH) algorithm is a novel swarm intelligent algorithm which is inspired the herding behavior of the krill swarms. The various test results in the relevant literature show that the KH algorithm has better performance than the other swarm intelligent algorithm for optimization problem. In order to further improve the performance of the KH algorithm, an improved KH is proposed in this paper. The algorithm is performed on ten test functions and the results are compared with the basic KH algorithm, PSO, DE and GA algorithm. The experimental results indicate that the improved algorithm is a good method for numerical optimization problem.

Keywords: *Swarm intelligence algorithm, Krill herd algorithm, numerical optimization*

1. Introduction

In mathematics research, optimization is defined as the selection of the best solution from some set of available alternatives. In other words, the optimization is to obtain the optimal solution by maximizing or minimizing a real function given a defined domain within an allowed set and computing the value of the function.

Over the years, various optimization algorithms have been presented by a number of scholars and researchers. The traditional algorithms are especially suited for simple optimization problem, but the computational complexity may be excessively high for some complex optimization. To solve the problem, heuristic algorithms are applied to find the optimal solutions for the optimization problem. At present, many heuristic algorithms have been presented, such as differential evolution (DE) algorithm [1-3], Genetic algorithms (GA) [4-6], Particle swarm optimization (PSO) [7-10], Artificial bee colony optimization (ABC) [11,12] *etc*.

Islam et al. proposed a novel mutation and crossover strategies for differential evolution (DE) algorithm, the comparative results demonstrates that the improved DE algorithm is better for Global Numerical Optimization [13]. Leung et al. designed the orthogonal genetic algorithm with quantization for global numerical optimization, and the experiments demonstrated that the improved algorithm can find optimal or close-to-optimal solutions than the basic genetic algorithm [14]. The researcher Liang et al. presented a variant of particle swarm optimizers (PSOs) call the comprehensive learning particle swarm optimizer (CLPSO), the results show that the CLPSO algorithm has good performance in solving multimodal problems compared with the PSO [15]. The researcher Vesterstrom et al. applied DE and PSO algorithm to the numerical benchmark problems. The results show that DE and PSO have better performance and DE outperforms the PSO algorithm [16]. Karaboga et al. used the ABC algorithm for optimizing multivariable functions and compared with the PSO, GA and Particle Swarm

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Inspired Evolutionary Algorithm (PS-EA) algorithm. The experimental results demonstrated that the ABC algorithm is better than the other algorithms [17].

The krill herd algorithm is new heuristic algorithms presented for solving optimization tasks in 2012[18]. In the algorithm, three main factors define the position of the krill individuals that are movement induced by the presence of other individuals, foraging activity, and random diffusion [18-22]. The KH algorithm has better performance for optimization problem, but sometimes it may trap into the local optima. In this paper, an effective krill herd algorithm is proposed for numerical optimization. In KH algorithm, ω_n is the inertia weight of the motion that is in the range of $[0,1]$, a new update method of ω_n is presented. Then the performance of the improved KH algorithm is tested on ten test functions.

The rest of this paper is organized as follows: Section 2 describes the basic KH algorithm. In Section 3, the improved KH algorithm is presented in detail. Section 4 draws a lot of the simulation results and also gives the discussions. In Section 5, the summary is drawn.

2. Brief Explanations of the Basic Krill Herd Algorithm

The Krill herd algorithm is a new optimization algorithm which is inspired the behavior of the krill swarms.

Through an investigation of the herding behavior of krill swarms, the researchers find that the movement of krill swarms is to reach two main goals: (1) increasing krill density, and (2) reaching food, so the herding behavior of increasing density and finding food is considered as a constrained optimization process.

The location of a krill individual is affected by the following three factors: (1) Movement induced by other krill individuals; (2) Foraging activity; and (3) Random diffusion. So the location of the krill is expressed by the following Lagrangian model:

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

Where N_i is the motion led by other krill individuals, F_i is the foraging motion, and D_i is the physical diffusion of the i th krill individual.

In the movement, the direction of motion of a krill individual is determined both by the local swarm density (local effect), a target swarm density (target effect), and a repulsive swarm density (repulsive effect). The expression of movement is presented as:

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

Where $\alpha_i = \alpha_i^{local} + \alpha_i^{target}$ $N^{\max}$, ω_n and N_i^{old} are the maximum induced speed, the inertia weight of the motion that is in the range of $[0,1]$, the last motion induced, respectively.

The motion of a krill herd is influenced by two main effective factors: (1) the food location; and (2) the previous experience about the food location. The expression of the motion can be stated as:

$$F_i = V_f \beta_i + \omega_f F_i^{old} \tag{3}$$

Where V_f, ω_f and F_i^{old} are the forging speed, the inertia weight of the foraging motion, the last one, respectively.

The physical diffusion of the krill individuals is a random process, and the motion associates with maximum diffusion speed and random directional vector. The equation of the physical diffusion can be defined by:

$$D_i = D_{\max}\delta \tag{4}$$

Where D_i is the maximum diffusion speed, δ is the random directional vector and its arrays are random values in $[-1,1]$.

The motion of krill swarm can be considered as a process toward the best fitness. So the position of a krill individual can be given by:

$$X_i(t+\Delta t) = X_i(t) + \Delta t \frac{dX_i}{dt} \tag{5}$$

The parameter Δt is very important that can be treated as a scale factor of the speed vector. So it must be adjusted in terms of the optimization problem. The value of Δt is completely depends on the given search space.

3. Improved Krill Herd Algorithm

Begin
Step 1: Initialization. Set the generaton counter t=1; initialize the population of krill randomly; set the foraging speed V_f, the maximum diffusion speed $D_{\max}$, the maximum induced speed $N_{\max}$, and the intertia weights.
Step 2: Fitness evaluation. Evaluate each krill individual according to its position.
Step 3: While (t < MaxGeneration) *do*
Sort the krill from best to worst.
Update the inertia weights using the Eq.(6)

$$\omega_n = 0.9 - \frac{t*(0.9-0.1)}{MaxIteration}$$

for $i = 1 : N$ (all krill) *do*
Perform three motions.
Update the krill position.
Compute their fitness for all krill.
end for i
Sort the population and find the current best.
$t = t+1$;
Step 4: end while
Step 5: Output the best solution.
End.

Figure 1. The Basic Step of the New KH Algorithm

In the KH algorithm, the inertia weight of the motion ω_n is an important parameter that decides the direction of motion of krill individual. The inertia weight is in the range of $[0,1]$ in the basic KH algorithm. In order to achieve a good balance between two processes of exploration and exploitation, a new update pattern ω_n is proposed that vary with the iterations in this section. We make ω_n have the following expression:

$$\omega_n = 0.9 - \frac{t*(0.9-0.1)}{MaxIteration} \tag{6}$$

Where t is the iteration, and $MaxIteration$ is max iteration. The basic steps of the new KH algorithm are shown as Figure 1.

4. Experiments and Discussion

The optimization problem can be considered as minimization and maximization problem. Let there be a function $f(x)$, a set A and an element x_0. For x all in A, the expression of minimization is stated as follows:

$$f(x_0) \le f(x) \tag{7}$$

For the maximization problem, it can be represented as:

$$f(x_0) \ge f(x) \tag{8}$$

In this section, a very large number of experiments are carried out. These experiments are done by MATLAB Release 2010. The performance of the algorithm for numerical optimization problems is tested for ten standard test functions. The test benchmark functions and their corresponding domains, optimal values and dimension are shown in Table 1. In all experiments, the population size is set to 25 for the KH and improved KH algorithm, the max iteration is 100, the foraging speed $V_f = 0.02$, the maximum diffusion speed $D^{\max} = 0.005$, the maximum induced speed $N^{\max} = 0.01$, the intertia weights (ω_n, ω_f) is the range of $[0.1, 0.9]$.

4.1. Comparison with the Basic KH Algorithm

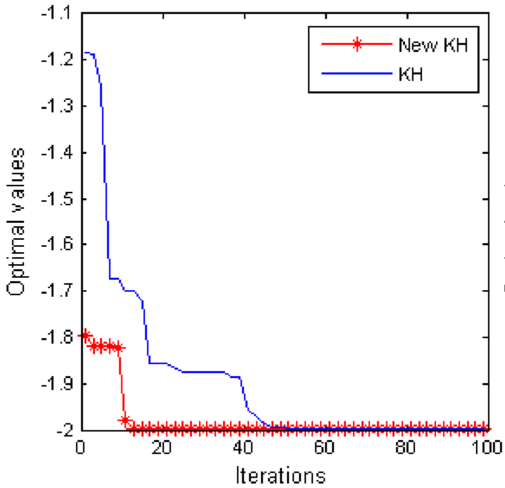
In the first part of experiments of this section, the new KH algorithm presented in this paper is compared with the basic KH algorithm. The two algorithms are applied to ten test functions. The best values, worst values, mean values and standard deviation are drawn in Table 2. The experiments are independently done 30 times for the each test function. From the results of Table 2, it is clearly shown that the improved KH algorithm can obtain better best value, worst value and mean value of the objective function than the basic KH algorithm for all the test functions. The values of standard deviation values in Table 2 indicate that the new KH algorithm possesses better robustness than the basic KH algorithm.

Table 1. Benchmark function

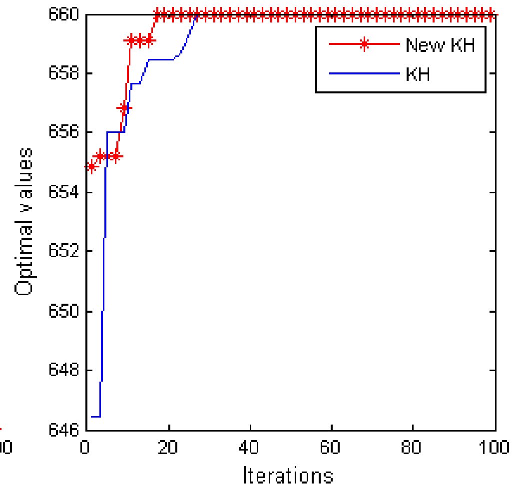
Functions	domains	Optimal value	Dimension
$f_1(x) = x_1^2 + x_2^2 - \cos(18x_1) - \cos(18x_2)$	[-1,1]	-2	2
$f_2(x) = 660 - (x_1^2 + x_2 - 11)^2 - (x_1 + x_2^2 - 7)^2$	[-6,6]	660	2
$f_3(x) = (x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6)^2 + 10(1 - \frac{1}{8\pi})\cos x_1 + 10$	[-5,15]	0.397887349	2
$f_4(x) = (x_1 + 2x_2 - 7)^2 + (2x_1x_2 - 5)^2$	[-10,10]	0	2
$f_5(x) = (\cos x_1 \cos x_2)e^{-(x_1-\pi)^2-(x_2-\pi)^2}$	[-20,20]	1	2
$f_6(x) = \sum_{i=1}^{n} i x_i^2$	[-5.12,5.12]	0	30
$f_7(x) = \sum_{i=1}^{n}(0.2x_i^2 + 0.1x_i^2 \sin 2x_i)$	[-10,10]	0	30
$f_8(x) = \sum_{i=1}^{n}(x_i + 0.5)^2$	[-10,10]	0	30
$f_9(x) = \sum_{i=1}^{n} x_i^2$	[-100,100]	0	30
$f_{10}(x) = \sum_{i=1}^{n}(x_i^2 - 10\cos(2\pi x_i) + 10)$	[-100,100]	0	30

Table 2. Comparison of Basic KH and the New KH Algorithm

Functions	Algorithm	Best value	Worst value	Mean value	Standard deviation
f_1	KH	-1.9999999999	-1.9999999976	-1.9999999988	7.13E-10
	New KH	-2.0000000000	-1.9999999986	-1.9999999997	5.01E-10
f_2	KH	659.9999999997	659.9999999760	659.9999999933	6.92E-09
	New KH	660.0000000000	659.9999999916	659.9999999956	3.09E-09
f_3	KH	0.3978873490	0.3978873434	0.3978873484	1.67E-09
	New KH	0.3978873490	0.3978873482	0.3978873489	2.42E-10
f_4	KH	2.93E-11	6.52E-08	2.48E-08	2.31E-08
	New KH	2.88E-11	2.84E-08	1.61E-08	9.64E-09
f_5	KH	0.9999999999	0.9999999993	0.9999999995	3.82E-11
	New KH	1.0000000000	0.9999999992	0.9999999999	1.98E-11
f_6	KH	1.07E-15	1.35E-12	3.66E-13	4.90E-13
	New KH	7.37E-17	3.88E-13	1.06E-13	1.33E-13
f_7	KH	1.68E-15	6.26E-13	8.03E-14	1.84E-13
	New KH	1.62E-16	6.47E-15	2.42E-15	2.19E-15
f_8	KH	1.36E-15	7.81E-13	1.03E-13	6.95E-14
	New KH	3.10E-15	9.58E-15	2.56E-15	3.45E-15
f_9	KH	8.40E-14	2.82E-11	5.92E-12	8.28E-12
	New KH	1.03E-15	1.96E-11	3.65E-12	5.99E-12
f_{10}	KH	2.10E-11	1.96E-08	5.38E-09	4.12E-09
	New KH	1.09E-11	8.08E-09	1.39 E-09	2.43E-09

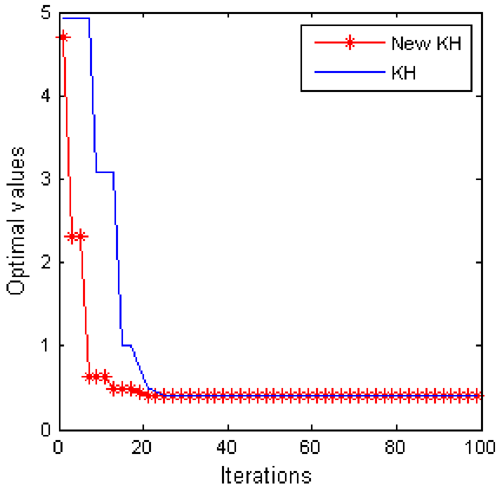


(a)

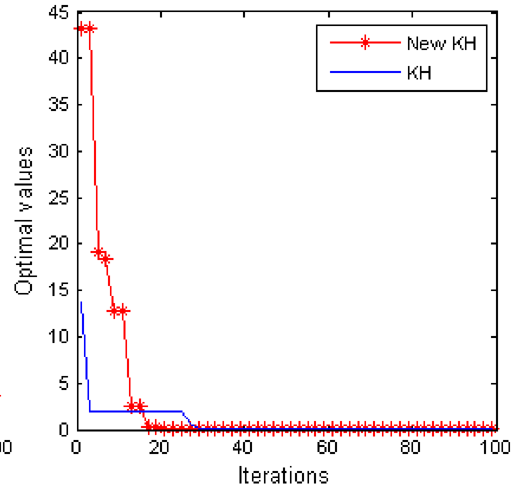


(b)

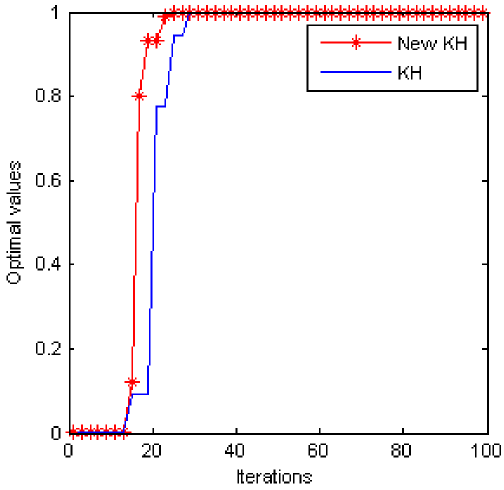
In the second part of experiments of this section, in order to compare the performance for optimization, the convergence curves of the best value for $f_1 - f_{10}$ test functions using KH and new KH algorithm are drawn in Figure 2. From the results of the Figure 2, it reveals that the improved KH algorithm can find the optimal objective values quickly than the basic KH algorithm for all the test function and has better convergence rate for the low dimensional and high dimensional function test functions.


New KH
KH
Optimal values
Iterations

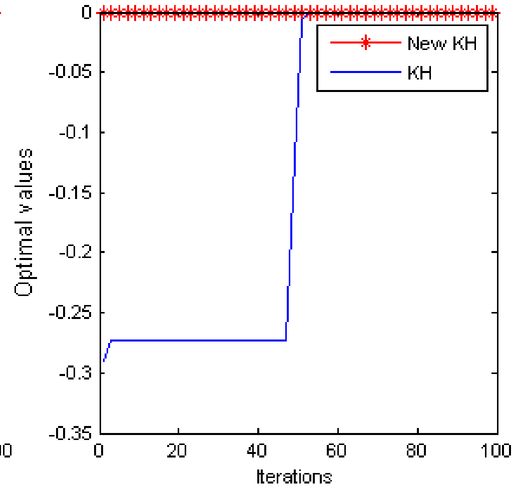
(c)


New KH
KH
Optimal values
Iterations

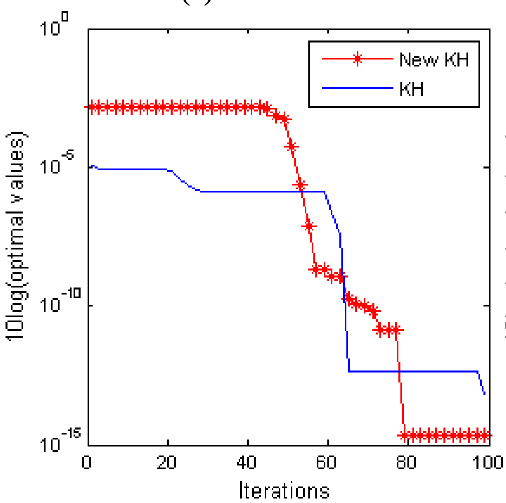
(d)


New KH
KH
Optimal values
Iterations

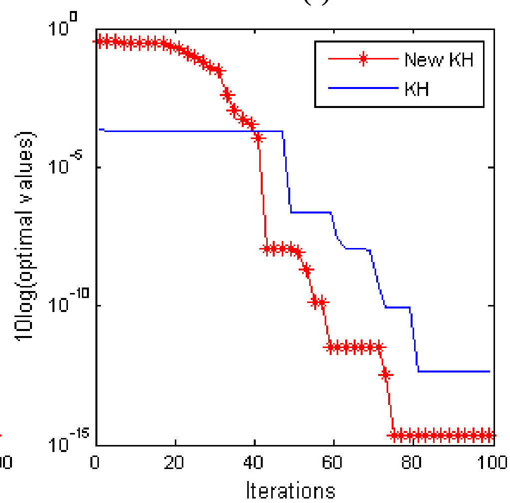
(e)


New KH
KH
Optimal values
Iterations

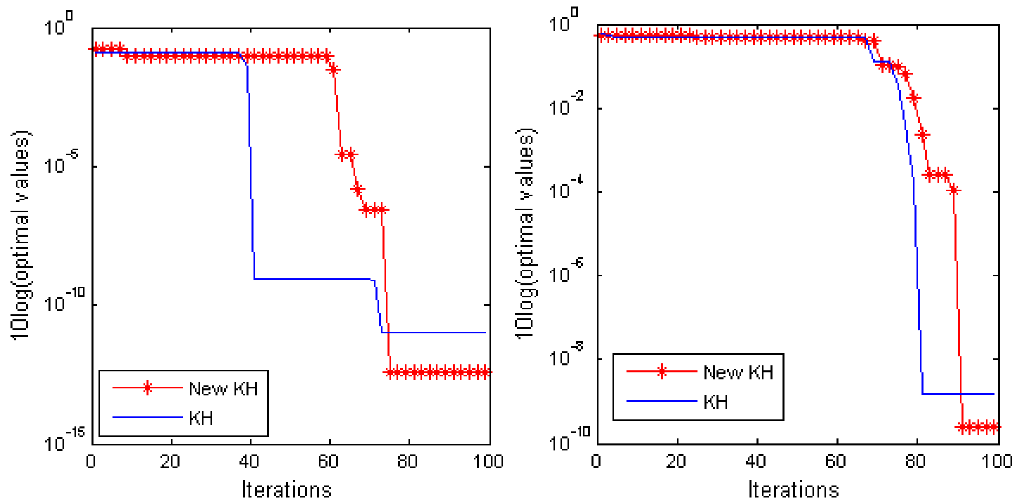
(f)


New KH
KH
10log(optimal values)
Iterations

(g)


New KH
KH
10log(optimal values)
Iterations

(h)



(i) (j)

Figure 2.The Convergence Curve of Best Value for $f_1 - f_{10}$ Using KH and New KH Algorithm

From the Table 2 and Figure 2, the results show that the new KH is superior to the basic KH algorithm for numerical optimization.

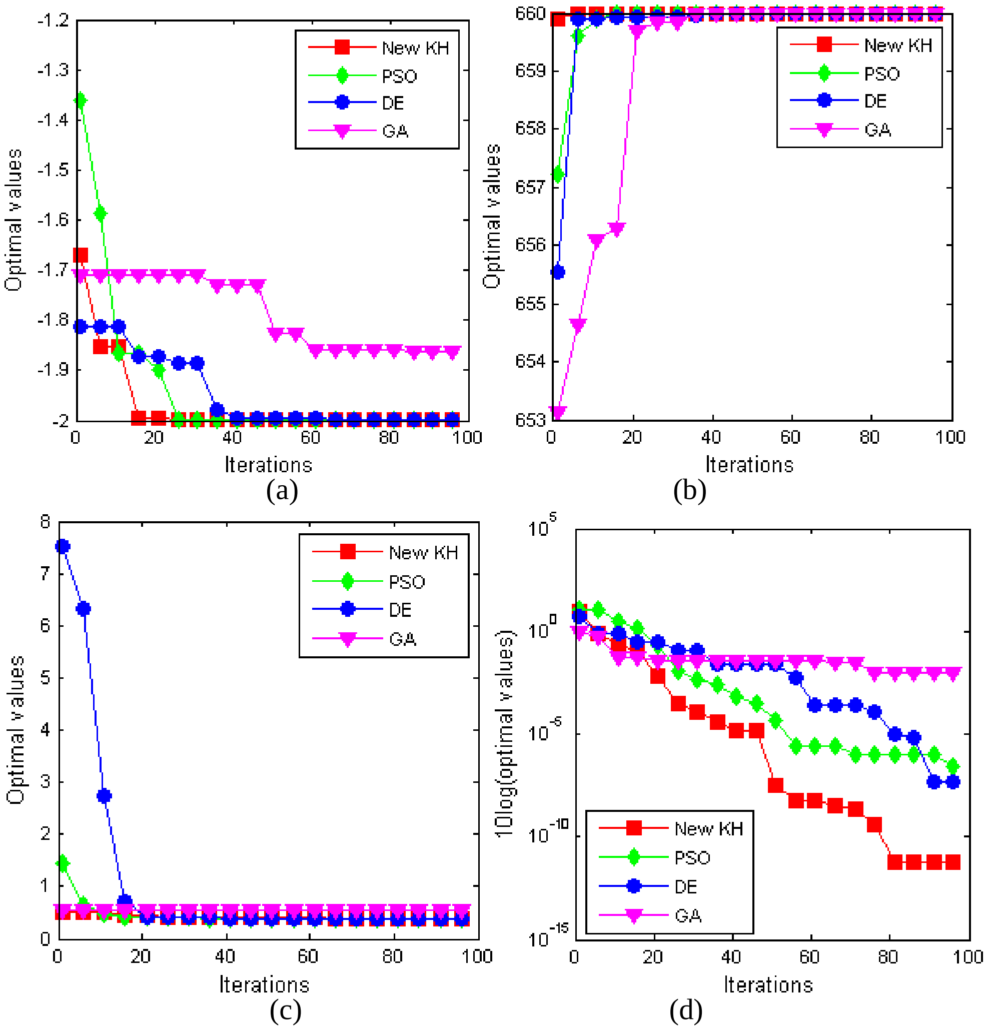
4.2. Comparison with Other Algorithm

In this section, the new KH algorithm is compared with the particle swarm optimization (PSO), differential evolution (DE) and genetic algorithm (GA) and the algorithms are also tested on the ten test functions. The results of the mean values and standard deviation values are given in Table 3. The results show that the new KH algorithm provide better performance for all the functions than PSO, DE and GA algorithm. Figure 3 present the convergence curves of the best value for the ten test functions. It can be observed that the convergence curves of the new KH algorithm descend much faster and reach better optimal values than PSO, DE and GA algorithm.

Table 3. Comparison with the Other Algorithm

Functions	Measure	GA	PSO	DE	New KH
f_1	Mean	-1.9927430168	-1.9999999993	-1.9999999987	-1.9999999997
	Standard deviation	5.47E-05	1.30E-09	2.32E-09	5.01E-10
f_2	Mean	659.9979928991	659.9999999953	659.9999999952	659.9999999956
	Standard deviation	5.93E-06	3.89E-09	3.49E-09	3.09E-09
f_3	Mean	4.0070925131	3.978873449	3.978873483	0.3978873489
	Standard deviation	3.13E-03	2.44E-09	2.60E-09	2.42E-10
f_4	Mean	6.43E-03	3.05E-06	2.78E-06	1.61E-08
	Standard deviation	7.19E-04	3.01E-08	2.25E-08	9.64E-09
f_5	Mean	0.9999999993	0.9999999999	0.9999999999	0.9999999999
	Standard deviation	9.02E-10	3.52E-11	3.99E-11	1.98E-11
f_6	Mean	1.25E-03	3.49E-05	8.23E-07	1.06E-13
	Standard deviation	1.27E-03	4.23E-05	1.91E-06	1.33E-13

f_7	Mean	5.16E-03	9.75E-07	5.36E-06	2.42E-15
	Standard deviation	7.19E-02	2.25E-06	4.73E-06	2.19E-15
f_8	Mean	3.19E-03	1.22E-07	2.01E-06	2.56E-15
	Standard deviation	4.08E-03	2.26E-07	9.28E-07	3.45E-15
f_9	Mean	1.03E-02	5.73E-04	4.74E-06	3.65E-12
	Standard deviation	1.84E-02	1.35E-03	4.57E-06	5.99E-12
f_{10}	Mean	5.27E-01	6.983E-04	1.35E-02	1.39E-09
	Standard deviation	3.26E-01	5.93E-04	2.14E-02	2.43E-09



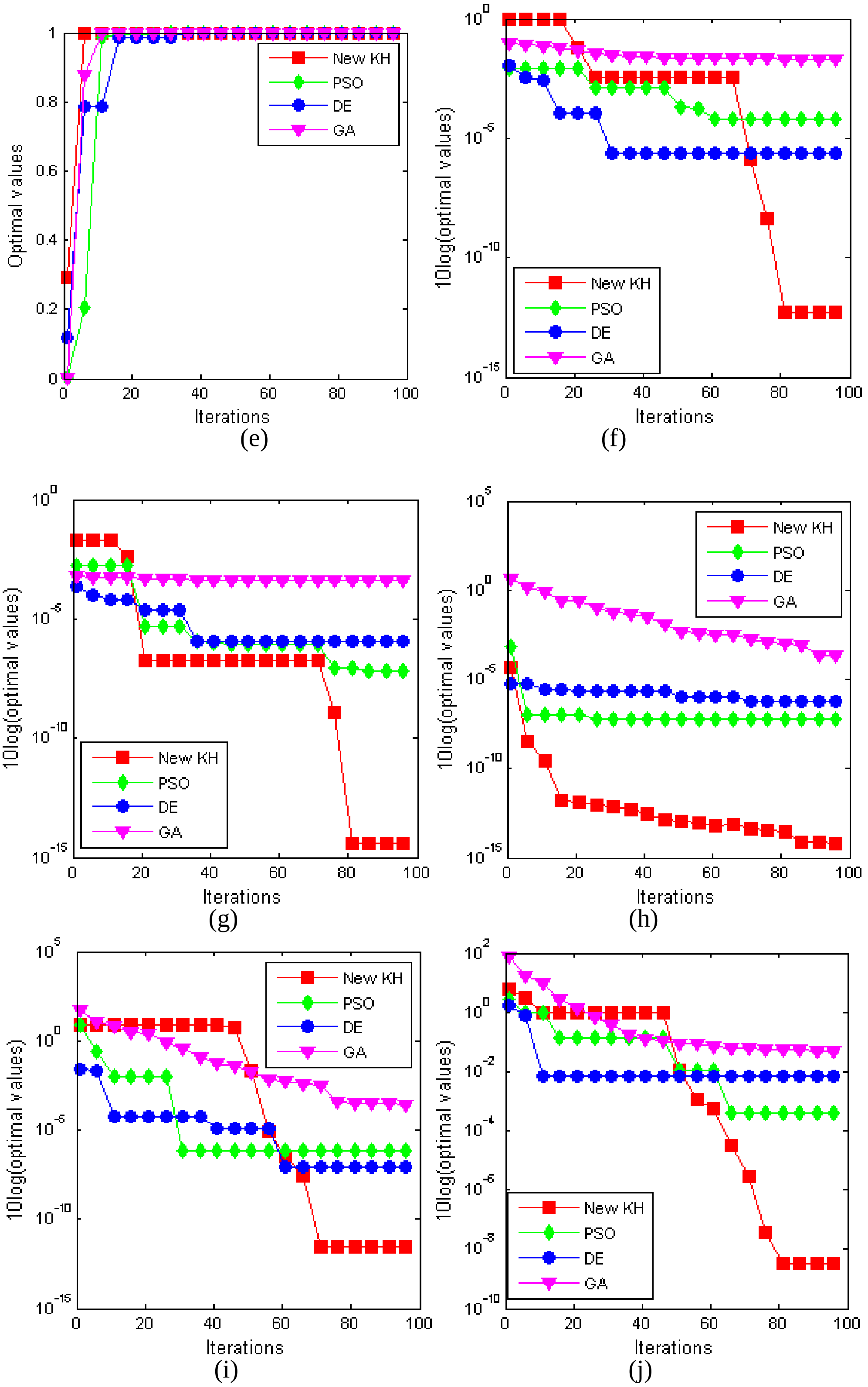


Figure 3.The Convergence Curve of New KH, PSO, DE and GA Algorithm For $f_1 - f_{10}$

5. Summary

In this paper, an improved KH is presented which introduced the update method of ω_n to the basic KH algorithm. The new KH algorithm is used for the numerical optimization problem. In order to verify the performance of the presented algorithms,it is tested on the ten test function and the performance is compared with the basic KH algorithm, PSO,DE and GA algorithm.The simulation results show that the improved KH has better performance and is a better method for numerical optimization problem. In the future, our work will focus on the improvement of the KH algorithm and the application for the other complex optimization problems.

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