

A Comparison of HPSOWM, Krill Herd and Spider Monkey Optimization Algorithms

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Abstract— Hybrid Particle Swarm Optimization with Wavelet Mutation (HPSOWM), Krill Herd & Spider Monkey optimization algorithms are recent algorithms proposed for numerical optimization. In this paper their performance across various benchmark functions is evaluated. A t-test is used to compare the statistical significance of the results.

Keywords- *Swarm Intelligence, Numerical optimization, HPSOWM, Krill Herd optimization, Spider Monkey optimization.*

I. INTRODUCTION

A Swarm in Biology refers to a collection of creatures (ants, bees, birds etc). Man has always been fascinated by social behaviors of these creatures and their ability to solve complex problems in their natural habitat. The Particle Swarm Optimization [1] by Kennedy et al. was originally an effort to simulate social behavior of bird flocks and fish school; however they discovered that a simplified version of the algorithm was suitable for performing numerical optimization.

Swarm behavior based algorithms have been used in recent literature to solve problems ranging from healthcare [2, 5] to Industrial applications [3, 6]. As a consequence of No Free Lunch Theorem [5] it's clear that no single optimization algorithm exists which can solve all optimization problems and therefore many such algorithms have been proposed in recent literature [3,7,8,9,14,15] making this field a highly active one. Therefore it becomes important to compare and contrast these algorithms and many such attempts exist in literature [11-13, 18]. Our paper compares three such recent Swarm Algorithms namely HPSOWM [3], Krill Herd Algorithm [8] and The Spider Monkey Optimization Algorithm [9].

II. SUMMARY OF ALGORITHMS

In this section we give a brief explanation to all three algorithms.

A. HPSOWM

The HPSOWM [3] by Ling et al introduced a new mutation operator to solve industrial applications such as load flow problems and developing a neural network based controller.

It incorporates wavelet theory to provide a stable and high quality solution and helps to avoid local minima in many multimodal benchmark functions.

Let $x^p(t)$ represent the D dimensional p^{th} particle given by (1).

$$x^p(t) = [x_1^p(t), x_2^p(t), x_3^p(t) \dots x_D^p(t)] \quad (1)$$

The mutation operator can be applied to any random dimension of every particle (2) just after PSO iteration according to probability of mutation pm defined by the user. The operations are defined as under

$$x_j^p(t) = \begin{cases} x_j^p(t) + \sigma * [upper_j - x_j^p(t)] & \text{if } \sigma > 0 \\ x_j^p(t) + \sigma * [x_j^p(t) - lower_j] & \text{if } \sigma \leq 0 \end{cases} \quad (2)$$

Where $upper_j$ and $lower_j$ are respectively the upper and lower bound for that dimension and σ is given by (3).

$$\sigma = \frac{1}{\sqrt{a}} e^{-0.5(\frac{\varphi}{a})^2} \cos(5\frac{\varphi}{a}) \quad (3)$$

Where a is given by (4) and φ is a random number

between 0 and 1.

$$\alpha = e^{-(\ln g) * (1 - \frac{t}{T})^{twm} + (\ln g)} \quad (4)$$

The parameters pm, g and twm are to be defined by the user and depend upon the optimization problem at hand.

B. Krill Herd Algorithm

Gandomi and Alavi proposed the Krill Herd Algorithm [8] in 2012 and many variants have been proposed namely the Chaotic Krill herd [10]. This algorithm simulates the behavior of Krill individuals in a herd. There are three main activities of Krill which is incorporated into the algorithm namely

- Induced movement (N)
- Foraging motion (F)
- Random Diffusion (D)

Induced movement corresponds to density maintenance.

$$N_i(t+1) = N_{max} \alpha_i + \omega_n N_i(t) \quad (6)$$

$$\alpha_i = \alpha_i^{target} + \alpha_i^{local} \quad (7)$$

The maximum induced speed is denoted by N_{max} and ω_n indicates the inertia weight, α_i^{local} shows the local effect of neighbours of i^{th} krill individual and best solution is denoted by α_i^{target} . Here r is a random variable between 0 and 1.

$$\alpha_i^{target} = C^{best} K_{i,best} X_{i,best} \quad (8)$$

$$C^{best} = 2 \left(\frac{r+1}{I_{max}} \right) \quad (9)$$

Equation (10) indicates the foraging behavior. In this V_f is the foraging speed, ω_f is the inertia weight β_i^{food} is the food attractiveness and B_i^{best} is the best solution for i^{th} krill.

$$F_i(t+1) = V_f \beta_i + \omega_f F_i(t) \quad (10)$$

$$\beta_i = \beta_i^{food} + B_i^{best} \quad (11)$$

The Third activity of Krill is random diffusion given by (12). Here δ is a random directional vector between $[-1, 1]$.

$$D_i(t+1) = D^{max} \left(\frac{1-l}{I_{max}} \right) \delta \quad (12)$$

The position update of the krill individual is given by

$$Xp_i(t+1) = Xp_i(t) + \Delta xp_i(t) \quad (13)$$

$$\Delta xp_i(t) = N_i(t) + F_i(t) + D_i(t) \quad (14)$$

The final position of the krill individual is given by (13).

C. Spider Monkey Optimization

Spider Monkey Optimization (SMO)[9] is an iterative algorithm that uses a trial and error based and collaboration technique. The algorithm has six steps namely

- Local Leader Selection (LLS)
- Global Leader Selection (GLS)
- Local Leader Learning (LLL)
- Global Leader Learning (GLL)
- Local Leader Decision (LLD)
- Global Leader Decision (GLD)

Let N be the no of spider monkeys where each monkey is referred to as M_k ($k=1,2,\dots,N$) and is a vector of D elements (dimensions) where each element is represented as D_l ($l=1,2,\dots,D$). The position of each M_k is a probable solution to the problem. The Location of each monkey is initialized as

$$M_{k,l} = M_{min,l} + R * (M_{max,l} - M_{min,l}) \quad (15)$$

Where R is a random number drawn from uniform distribution with values varied between 0 to 1, $M_{max,l}$ and $M_{min,l}$ are the upper and lower bound for that dimension. In LLS monkey modifies its location using the information provided by the leader and local group members. For a group k the position is updated as

$$M_{new\ i,j} = M_{i,j} + R * (Leader_{k,j} - M_{i,j}) + R(-1,1) * (M_{r,j} - M_{i,j}) \quad (16)$$

Where $Leader_k$ is leader of group k and r is random member of group k . If new position has better cost then it is accepted else rejected. In GLS monkeys update their location using information provided global leader and local group members. The position are updated using $prob_i$ that is

$$prob_i = 0.9 * \frac{fitness}{max_fitness} + 0.1 \quad (17)$$

where fitness is the fitness of i^{th} Monkey and $max_fitness$ is highest fitness among all monkeys. The updation takes place according to (18).

$$M_{new\ i,j} = M_{i,j} + R * (GL_{k,j} - M_{i,j}) + R(-1,1) * (M_{r,j} - M_{i,j}) \quad (18)$$

Where $GL_{k,j}$ the j^{th} dimension of global leader and r is random member of group k . In GLL and LLL, greedy selection is used to update global leader and local leaders after

every iteration. In LLD step in the local leader is not updated over a threshold after specific threshold (LocalLeaderLimit) then group's positions are updated randomly or information from both Global Leader and Local Leader as follows

$$M_{new\ i,j} = M_{i,j} + R * (GL_{k,j} - M_{i,j}) + R(-1,1) * (M_{r,j} - LL_{k,j}) \quad (19)$$

GLD is similar to LLD but instead of local leaders the global leader is monitored with max iterations referred to as GlobalLeaderLimit. In case the limit is reached then the group is split into smaller groups unless we reach the max groups possible MG.

III. T-TEST

A T test can be used to evaluate the difference between two algorithms [3]. A positive value indicates that the former is better than the latter and a negative indicates that latter is better.

$$t = \frac{\alpha_2 - \alpha_1}{\sqrt{\frac{\rho_1^2}{\varepsilon+1} + \frac{\rho_2^2}{\varepsilon+1}}} \quad (20)$$

The t value is given by equation ε is the no of free parameters α_1 and α_2 indicates the mean and ρ_1 and ρ_2 indicates the variances respectively.

IV. RESULTS AND DISCUSSION

We simulated all three algorithms 100 times (100 iterations) on three benchmark functions namely Sphere ,Rastrigin and,Griewank functions (appendix-1). The results have been summarized in Table 1 the no of dimensions of the solution are selected to be 30 and the optimal fit value is 0. The box plots for the simulations can be seen in (1-3)

Furthermore, a T test has been used to compare three algorithms and the results have been summarized as in Table2.

A T value greater than 1.645 indicates a >95% significance that the first algorithm is better than the second. The results indicate that for the Griewank function, the Spider Monkey algorithm is significantly better than the others while in the case of Rastrigin and the Sphere function HPSOWM significantly outperforms the rest. Also we note that the standard deviation for the Krill herd algorithm is smaller in comparison to HPSOWM and SM in the case of sphere and Rastigin function and it outperforms the spider monkey algorithm in the case of sphere function. Also in case of the Griewank function even though best solution is lower in case of HPSOWM the mean solution is higher this is also reflected in the T-value We note that the parameter selection for HPSOWM is difficult as compared to SM or KH but it outperforms them for most problems observed here. For HPSOWM these parameter values can be adjusted according to the domain knowledge of the problem and the results may vary according to the chosen parameter settings.

TABLE 1 COMPARATIVE RESULTS

Function	Moments	HPSOWM	SM	KH
Sphere	Mean	0.0554	2.9132	0.1191
	Best	0.0087	0.7573	0.0430
	Std	0.0530	1.4214	0.0373
Rastrigin	Mean	3.1940	122.0918	5.5688
	Best	0.0279	86.7195	2.0460
	Std	2.2164	12.7389	1.3285
Griewank	Mean	0.0427	0.0348	0.1660
	Best	0.0072	0.0147	0.0876
	Std	0.0026	0.0137	0.0342

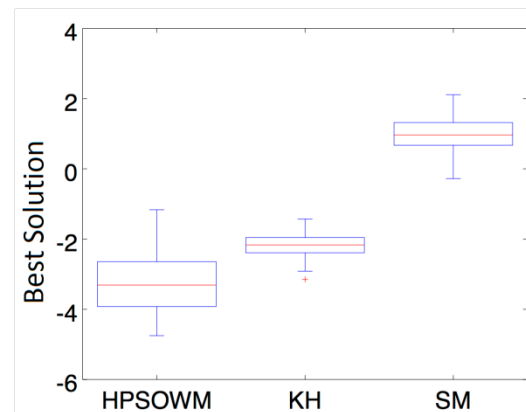


Fig 1 Box plot of best solutions attained for the Sphere Function

TABLE 2 T VALUES

Function	Algorithm 1	Algorithm2	T value
Sphere	HPSOWM	SM	10.0017
	HPSOWM	KH	144.0684
	SM	KH	-9.7785
Rastrigin	HPSOWM	SM	5.1784
	HPSOWM	KH	3.2170
	SM	KH	-5.0770
Griewank	HPSOWM	SM	-38.1302
	HPSOWM	KH	468.4562
	SM	KH	783.1384

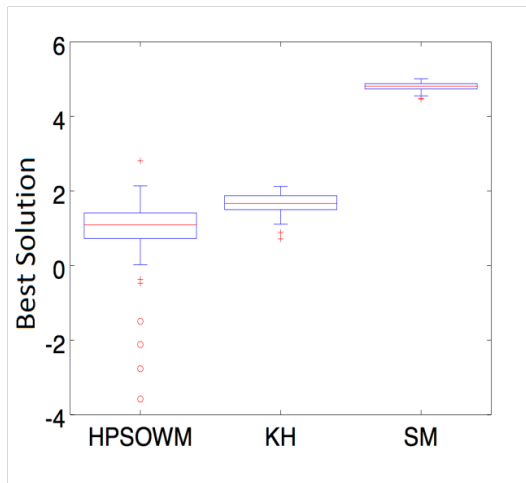


Fig 2 Box plot of best solutions attained for the Rastrigin Function

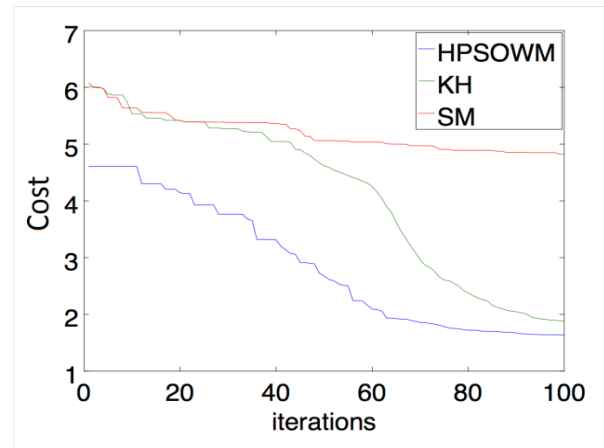


Fig 5 Cost function best solutions attained for the Rastrigin function

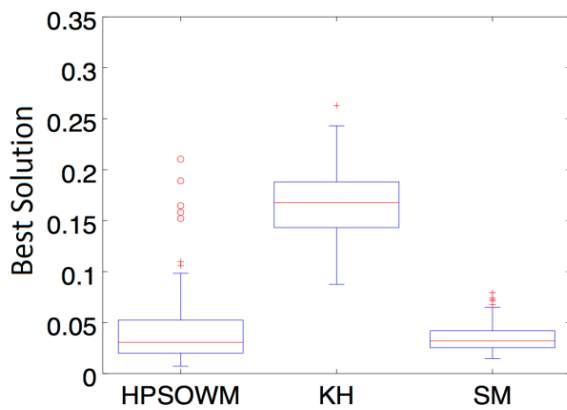


Fig 3 Box plot of best solutions attained for the Griewank function

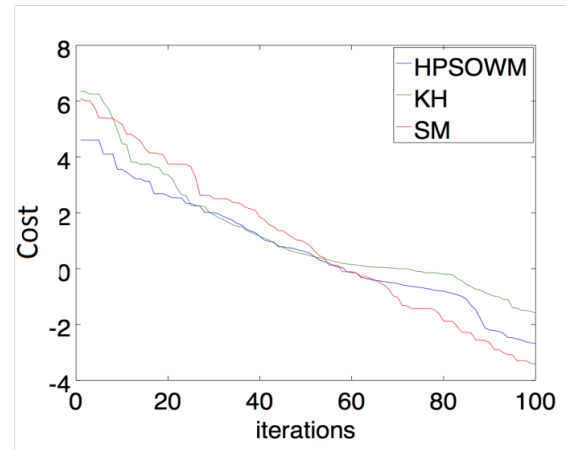


Fig 6 Cost function best solutions attained for the Griewank function

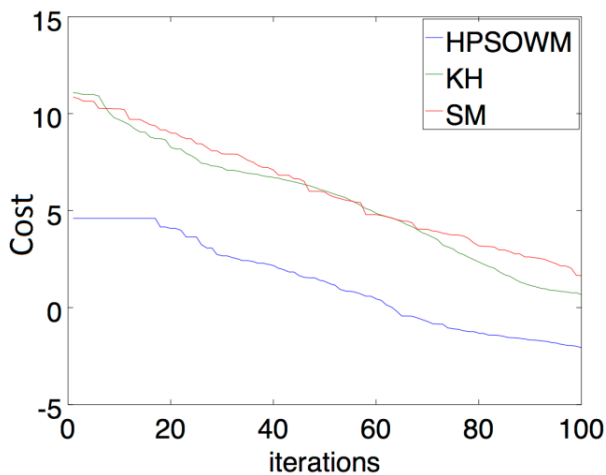


Fig 4 Cost function best solutions attained for Sphere function.

V. CONCLUSION

The way these algorithms traverse the search space is motivated by the social behavior of the creatures from which these were inspired for example the fission-fusion behavior of the Spider Monkey and the Krill herd motion. This greatly influences how they explore and exploit the search space and therefore we conclude that there is difference in their performance for different functions. This greatly stresses upon the need for new algorithms to be made and that their performance to be studied across different functions.

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Appendix-1 Benchmark Functions

Name	Function	Range
Sphere	$\sum_{j=1}^D x_j^2$	[100,100]
Rastigin	$\sum_{j=1}^D (x_j^2 - 10 \cos(10\pi x_j) + 10)$	[-5.12,5.12]
Greiwank	$\frac{1}{4000} \sum_{j=1}^D (x_j^2 - \prod_{j=1}^D \frac{x_j}{\sqrt{j}} + 1)$	[-600,600]

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