An Improved Spider Monkey Optimization Algorithm

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Chapter 1
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Abstract Spider Monkey Optimization is the newest member of the Swarm Intelligence based algorithm which is motivated by the extraordinary behavior of Spider Monkeys. The SMO algorithm is a population based stochastic meta-heuristic. The SMO algorithm is well balanced for good exploration and exploitation most of the times. This paper introduces an improved strategy to update the position of solution in Local Leader Phase. The proposed algorithm named as Improved Spider Monkey Optimization (ISMO) algorithm. This method is developed to improve the rate of convergence. The ISMO algorithm tested over the benchmark problems and its superiority established with the help of statistical results.

1.1 INTRODUCTION

Swarm Intelligence refer the natural system that are influenced by colonies of social insects like, fishes, bee, bird flocks, ant etc. The definition introduced by Bonabeau for the swarm intelligence is any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies [1]. These social creatures demonstrate some great ability while searching for food, security and mating in complex situations. The SMO algorithm is the latest population based strategy that is also stochastic in nature developed by J. C. Bansal et al. [2] to solve unconstrained optimization problems. The SMO is motivated by intelligent societal behavior of spider monkeys while searching for rich food sources. The SMO algorithm is based on fission-fusion

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structure of social living being spider monkey while searching for most suitable food source [2]. It consists of the intrinsic solution of population which denote food source of spider monkeys. The SMO Algorithm tries to keep proper balance between exploration and exploitation while searching for optimal solution. In exploitation it make sure that local optimum solution traversed properly and in exploration it explore global search space in order to avoid problem of trapping in local optimum. It has been observed that SMO is good in exploration of local search. The recent trend in research is inclined toward algorithms that are inspired by nature in order to solve complex real world problems that are not solvable by classical techniques. The nature inspired algorithms includes algorithms that are inspired by biological process, physical actions and other natural activities. These algorithms show some unconventional approaches that are able to solve optimization problems in field of science, engineering and management. Many researchers have analyzed the behavior and design of the algorithm that can be used to solve non-linear, non-convex, non-differential and multi-model problems. The SMO algorithm is comparatively young algorithm so there is not a large number of a literature. S.S. Pal et al. [3] used SMO algorithm in image segmentation and developed a new multi-level thresholding segmentation approach for gray scale images. K. Gupta et al. [4] carried out a comprehensive study of SMO after incorporating a new operator namely quadratic approximation and solved a large range of scalable and non-scalable benchmark problems and Lennard-Jones problem. A Sharma et al. [5] divided the population of spider monkeys into different age groups. It is assumed that younger monkeys are more interacting and frequently change their position in contrast to older monkeys. K. Gupta and K. Deep [6] introduced a new probability calculation approach namely tournament selection in SMO Algorithm. K. Gupta and K. Deep [7] analyzed the behavior of SMO algorithm under different perturbation rate schemes and proposed four editions of SMO are proposed analogous to constant, random, linearly increasing and linearly decreasing perturbation rate variation strategies. U. Singh et al. [8] developed a binary SMO algorithm and used it for thinning of concentric circular antenna arrays. U. Singh and R. Salgotra [9] introduced dual search strategy in SMO. The modified SMO used to synthesize linear antenna array. A. Sharma et al. [10] developed a new version of SMO with new local search strategy namely power law based local search. The new strategy was applied to solve model order reduction problem. A. A. Al-Azza et al.[11] introduces SMO algorithm for the electromagnetic and antenna community. P. Agarwal et al. [12] used social spider algorithm in image segmentation and developed a new multi-level thresholding segmentation approach for gray scale images by deploying histogram based bi-modal and multi-modal thresholding. S. Kumar et al. proposed three variant of SMO algorithm. Self-Adaptive Spider Monkey Optimization Algorithm for Engineering Optimization Problems [13] that require no manual setting, Fitness Based Position Update in Spider Monkey Optimization Algorithm [14] and Modified position update in spider monkey optimization algorithm [15]. The fitness based SMO update position of current swarm based on their fitness. It is assumed that highly fitted solution has good solution in their proximity. Almost all variant of SMO are better than other nature inspired optimization techniques (like: ABC, PSO etc.) in terms of efficiency, accuracy and robustness.

1.2 Spider Monkey Optimization

The SMO algorithm is a novel nature inspired algorithm which is developed by J. C. Bansal et al. in 2013 [2]. It is stochastic in nature as it introduced some random component in each step. The SMO strategy mimics the fission fusion structure of spider monkey. The major characteristics of fission fusion social structure are described as follow: Fission Fusion Social structure animals survive in group of forty to fifty monkeys that divides the member into subgroups for searching food in order to reduce competition. Global Leader (Female) is responsible for searching the food source that generally leads in the group. These groups are divided into small subgroup to search for food independently. Local Leader (Female) leads the subgroups and responsible for scheduling a well organized plan for foraging route each day. These group members search the food sources and modify their position based on the distance from food source. These group members communicate with all group members to maintain social bond in case of stagnation.

1.2.1 Phases of SMO Algorithm

The SMO algorithm consists of six major phases followed by initialization phases. These phases suggest that how spider monkey updates their position based on their previous experience and behavior of neighbors.

1.2.1.1 Initialization of the Population

In First, a population of N spider monkey is initialized. Initial population denoted by D-dimensional vector SM_i (i =1, 2... N). Every SMO represents the optimized solution of the problem under consideration. SM_i represents the population of spider monkey. SM_i is initialized as follow:-

$$SM_{ij} = SM_{minj} + \bigcup[0,1](SM_{maxj} - SM_{minj}) \ , \tag{1.1}$$

Where SM_{ij} represents the i^{th} food source in the swarm, SM_{minj} and SM_{maxj} are lower and upper bounds of SM_i in j^{th} direction respectively and U[0, 1] is a uniformly distributed random number in the range [0, 1].

1.2.1.2 Local Leader Phase (LLP)

The second phase is Local Leader Phase. This phase modernizes the location of SMO based on experience of Local and Global group members. These members compare fitness of new location and current location and apply greedy selection. Position update equation for i^{th} SM of K^{th} Group as follow:

$$SM_{newij} = SM_{ij} + \bigcup[0,1](LL_{kj} - SM_{ij}) + \bigcup[-1,1](SM_{rj} - SM_{ij}) , \tag{1.2}$$

Where SM_{ij} represents the i^{th} solution in j^{th} dimension, LL_{kj} denotes the j^{th} dimension of the k^{th} local group leader position. SM_{rj} is the r^{th} solution which is selected randomly from k^{th} group such as $r \neq i$. U [0, 1] is a uniformly distributed random number in the range of 0 to 1[2].

1.2.1.3 Global Leader Phase (GLP)

The GLP phase is just start after finishing the LLP. Position gets updated according to previous experience of the Global Leader and Local group members with the help of following equation.

$$SM_{newij} = SM_{ij} + \bigcup[0,1](GL_j - SM_{ij}) + \bigcup[-1,1](SM_{rj} - SM_{ij}) , \tag{1.3}$$

Where GL_j correspond to the j^{th} dimension of the global leader position and j 1, 2... D is randomly selected within dimension. In this phase, the Spider Monkey (SM_i) updates their position that is based on probabilities ($prob_i$) which are calculated using their fitness [2]. There may be different methods for probability calculation but it must be function of fitness. The fitness of a function indicates about its quality, fitness calculation must include function value.

$$prob_i = \frac{0.9 \times fitness_i}{fitness_max} + 0.1 , \tag{1.4}$$

1.2.1.4 Global Leader Learning (GLL) phase

In this phase SMO modify position of global leader with help of greedy approaches. Highly fitted solution in current swarm chosen as global leader. It also perform a check that the position of global leader is modernize or not and modify Global Limit Count accordingly [2].

1.2.1.5 Local Leader Learning (LLL) phase

Now in this phase modify location of local leader with help of greedy ap-proaches. Highly fitted solution in current swarm chosen as Local Leader. It also perform a check that the location of local leader is modernize or not and modify Local Limit Count accordingly [2].

1.2.1.6 Local Leader Decision (LLD) phase

During LLD phase decision taken about position of Local Leader, if it is not modernized up to a threshold a.k.a. Local Leader Limit (LL_{limit}). In case of no change it randomly initializes position of LL. Position of LL may be decided with the help of following equation.

$$SM_{newij} = SM_{ij} + \bigcup[0,1](GL_j - SM_{ij}) + \bigcup[0,1](SM_{ij} - LL_{kj}) \ , \tag{1.5}$$

It is clear from the above equation that the updated dimension of this SM is attracted towards global leader and repels from the local leader.

1.2.1.7 Global Leader Decision (GLD) phase

This phase takes the decision about position of Global Leader, if it is not modernized up to a threshold is known as Global Leader Limit (GL_{limit}), and then GLD creates subgroups of small size. During this phase, Local Leaders are created for new subgroups using LLL process[2].

1.3 An Improved Spider Monkey Optimization Algorithm

The Spider Monkey is a latest algorithm in different field of swarm intelligence. In literature there is very few research available on it. The newly proposed Improved Spider Monkey Optimization algorithm improves the performance of basic SMO algorithm. The ISMO suggested some improvement in Local Leader Phase of basic SMO. Position update equation in ISMO takes average of difference of current position and randomly generated positions. It generates a random position in given range for particular problem. This suggested modification accelerates the convergence rate and increase reliability. Here it is assumed that better fitted solution has optimal solution in their proximity.

$$Y_{ij} = X_{ij} + \phi_{ij}(LL_{kj} - ISM_{ij}) + \phi_{ij}\frac{SUM}{SN} \ , \tag{1.6}$$

Where

$SUM = SUM + X_{ij} - X_{kj}$, ϕ_{ij} is a uniformly generated random number in range [0,1].ISM_{ij} denotes the j^{th} dimension of the i^{th} ISM, LL_{kj} ensures the j^{th} dimension of the k^{th} local leader group location. The SN represents the food source that is randomly generated the position for food source. SUM is the average of difference for current position and random generated position. This equation updates highly fitted solutions through inspiration from best swarm intelligence. This new addition in SMO increases the balance between exploration and exploitation of most feasible solutions.

1.4 EXPERIMENTAL ANALYSIS

This paper checks the performance of Improved SMO algorithm over some well known benchmark optimization function f_1 to f_6. The performance of newly proposed algorithm is compared with Basic SMO [2]. The performance comparison is based on standard deviation (SD), Mean Error (ME), Average function evaluation (AFE) and Success Rate (SR).

1.4.1 Test problems under consideration

Problem 1 (Six-hump camel back): The Six hump camel back problem is formulated as follow:

$$f_1(x) = (4 - 2.1x_1^2 + x_1^4/3)x_1^2 + x_1x_2 + (-4 + 4x_2^2)x_2^2$$

The search boundary $[-5,5]$, the most feasible solution is $f(-0.0898, 0.7126) = -1.0316$, dimension of problem is 2 and acceptable error for successful run is fixed to be $1.0E-05$.
Problem 2 (Hosaki Problem): The Hosaki problem is defined as follow:

$$f_2(x) = (1 - 8x_1 + 7x_1^2 - 7x_1^3/3 + x_1^4/4)x_2^2 \times \exp(-x_2)$$

The search boundary $x_1 \in [0,5], x_2 \in [0,6]$, the most feasible solution is -2.3458, dimension of problem is 2 and acceptable error for successful run is fixed to be $1.0E-06$.
Problem 3 (Pressure Vessel design without Granularity): The problem of pressure vessel design formulated as follow:

$$f_3(\mathbf{x}) = 0.6224x_1x_3x_4 + 1.7781x_2x_3^2 + 3.1611x_1^2x_4 + 19.84x_1^2x_3$$

subject to

$$g_1(\mathbf{x}) = 0.0193x_3 - x_1 \leq 0$$

$$g_2(\mathbf{x}) = 0.00954x_3 - x_2 \leq 0$$
$$g_3(\mathbf{x}) = 750 \times 1728 - \pi x_3^2(x_4 + \frac{4}{3}x_3) \leq 0$$

Where x_1, x_2, x_3 and x_4 are thickness of shell, thickness of spherical head, radius of cylindrical shell and shell length. The search boundaries for the variables are

$$1.125 \leq x_1 \leq 12.5,$$

$$0.625 \leq x_2 \leq 12.5,$$
$$1.0 \times 10^{-8} \leq x_3 \leq 240$$

and

$$1.0 \times 10^{-8} \leq x_4 \leq 240.$$

The most feasible solution is $f(1.125, 0.625, 58.29016, 43.69266) = 7197.729$ [**?**]. Acceptable error for a successful run is fixed to be $1.0E-05$.

Problem 4 (Rosenbrock): The Rosenbrock problem with dimension 30 is defined as follow:

$$f_4(x) = \sum_{i=1}^{D-1}(100(x_i^2 - x_{i+1})^2 + (1-x_i)^2)$$

The search boundary $[-30, 30]$, the most feasible solution is $f(0) = 0$ and acceptable error for successful run is fixed to be $1.0E-01$.

Problem 5 (Salmon Problem): The Salmon problem with dimension 30 is defined as follow:

$$f_5(x) = 1 - \cos(2\Pi p) + 0.1 \times p, \text{where} p = \sqrt{\sum_{i=1}^{D}(x_i^2)}$$

The search boundary $[-100, 100]$, the most feasible solution is $f(0) = 0$ and acceptable error for successful run is fixed to be $1.0E-01$.

Problem 6 (Pathological Function): The Pathological function with dimension 30 is defined as follow:

$$f_6(x) = \sum_{i=1}^{D-1}(\frac{\sin^2(\sqrt{100x_{i+1}^2 + x_i^2}) - 0.5}{0.001(x_i - x_{i+1})^4 + 0.50}$$

The search boundary $[-100, 100]$, the most feasible solution is $f(0) = 0$ and acceptable error for successful run is fixed to be $1.0E-01$.

1.4.2 Experimental setting

The proposed ISMO algorithm compared with Basic SMO technique in order to prove its competence. It is programmed in C programming language with below mentioned experimental setting.

- The size of Swarm N=50,
- MG=5(Maximum group limiting maximum number of spider monkey in a group as MG=N/10),
- Global Leader Limit=50,
- Local Leader Limit=1500,
- $Pr \in [0.1, 0.4]$, linearly increasing over iteration.

1.4.3 Experimental Result Comparison

Table 1.1 Comparison of Result between SMO and ISMO

TP	Algorithm	MFV	SD	ME	AFE	SR
f_1	SMO	-1.03E+00	1.46E-05	1.90E-05	30783.45	41
	ISMO	-1.03E+00	1.52E-05	1.52E-05	22960.92	56
f_2	SMO	-2.35E+00	6.28E-06	6.04E-06	7831.09	85
	ISMO	-2.35E+00	6.06E-06	5.59E-06	3138.71	94
f_3	SMO	7.20E+03	9.49E-04	3.62E-04	28014.45	48
	ISMO	7.20E+03	3.35E-05	2.85E-05	23604.81	62
f_4	SMO	1.65E+00	1.03E+01	1.65E+00	14284.64	96
	ISMO	6.23E-02	5.22E-01	6.23E-02	11936.35	98
f_5	SMO	2.00E-01	7.80E-06	2.00E-01	6418.15	100
	ISMO	2.10E-01	3.00E-02	2.10E-01	15468.15	90
f_6	SMO	1.02E+00	4.47E-01	1.02E+00	50969.76	2
	ISMO	4.54E-01	3.41E-01	4.54E-01	38206.64	33

1.5 CONCLUSIONS

This paper proposed coherent and productive variant of SMO that improves the number of function evaluations in comparison to SMO Algorithm. By this algorithm we can find the feasible solution to understand the swarm intelligence based algorithm. This process is an extension of the position update in Local Leader Phase. This algorithm has been tested; it will increase the accuracy and reliability through the average of convergence rate comparison to SMO algorithm. This approach applied to the 6 benchmarks problems and results prove its superiority over basic SMO algorithm.

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